Demand-oriented irrigation water management in northwestern China : methodologies, empirics, institutions and policies

Tang, Jianjun

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Methodologies, empirics, institutions and policies

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by

Jianjun Tang

born on 1 August 1988
in Guangxi, China

Supervisor
Prof. H. Folmer

Co-supervisor
Prof. J. Xue

Assessment committee
Prof. C. Li
Prof. Z. Wang
Prof. D. Strijker

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Chapter 1

Introduction

1.1 Water scarcity in China

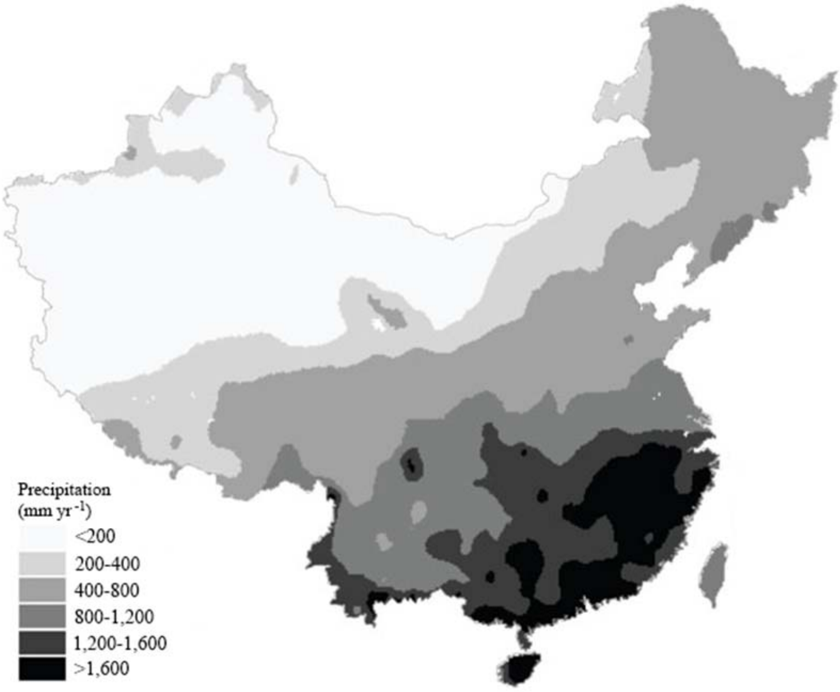
China's economy has been growing at an average rate of 10% a year since the economic reform in 1978 (NBSC, 2013). However, this unprecedented growth has been achieved at many social and environmental costs and has generated immense pressure on China's natural resources, especially water (Moore, 2013). Of China's 662 cities, 300 have been suffering from water shortage and 110 from severe water shortage (Li, 2006). A number of 27,000 rivers, more than 50% of China's total in the 1950s, has disappeared (The Economist, 2013). The share of crop areas hit by water shortage has increased by 16%, causing an annual loss of 27 million tons of yield (Chen et al., 2014). Former prime minister Wen Jiabao, summarized the problem by saying that water shortage is threatening "the very survival of the Chinese nation" (The Economist, 2013).

There are multiple reasons that have caused water shortage. First, China is endowed with limited water resources. Average annual water availability was 2,100 m^3 per capita in 2010, close to the threshold of water stress of 2,000 m^3 per capita[1]. Besides, water

[1] The UNDP, UNEP, World Bank and the World Resources Institute define 'water stress' as annual water availability between 1,000 and 2,000 m^3/person, and 'water scarcity' when availability is below 1,000 m^3/person (Shalizi 2006). The definition of "average annual water availability per capita" is a well-known yardstick for a region's water scarcity. See amongst others Jin and Young (2001) and Jiang (2009). It is a general measure referring to overall water availability for all users including households, industry, agriculture and ecosystems. There is no information on water availability for a single industry (or agriculture). Hence, the threshold of 2,000 m^3/person includes water available to households, industry, agriculture and ecosystems.

resources are unevenly distributed, both temporally and spatially (see Figure 1.1[2]). Water is abundant in the south but scare in the north. The North China Plain, known as the 3H (Huang Huai, and Haihe) river basin, contains 40% of China's arable land and produces 50% of its grain, but is endowed with only 8% of the national water resources. Annual water availability for the three basins is 672, 483 and 314 m^3 per capita, respectively, far below the water scarcity threshold of 1,000 m^3 per capita (Jiang 2009) (see Figure 1.2 for water resources per capita of China's river basins). Due to a continental monsoon climate, 60-70% of China's annual precipitation is concentrated in the June-September period. This percentage is close to 80% in northern regions. The temporal variation adds difficulties to utilize the water (Cheng et al., 2009). Particularly, in the wet season there is too much and in the dry seasons too little.

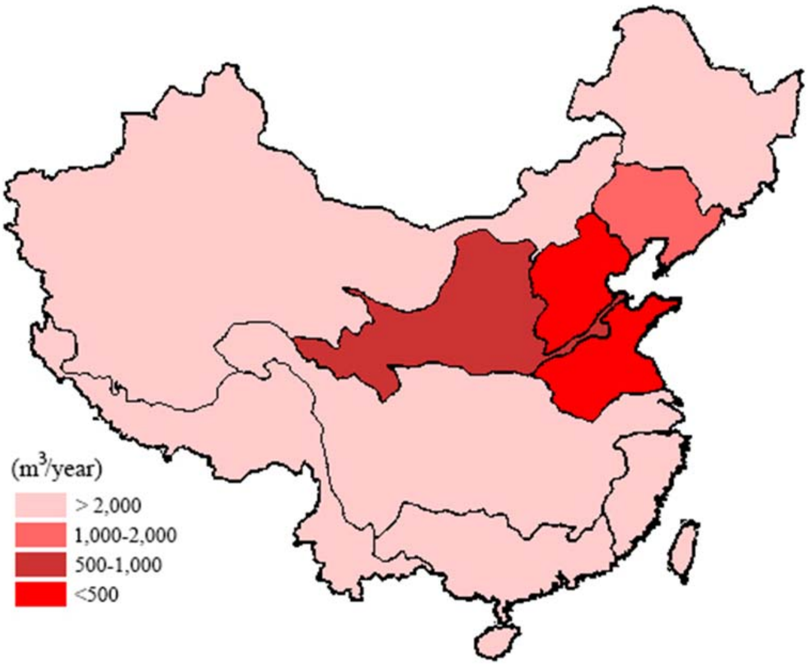
Figure 1.1 Annual precipitation in China



Secondly, demand for water has been growing rapidly from 443.7 km^3 in 1980 to 614.2 km^3 in 2012. Moreover, it is expected to continue to grow (Jiang, 2009). The main drivers of the rapidly growing demand for water have been population and income growth, industrialization and urbanization. The current population of 1.36 billion is expected to peak at 1.6 billion in 2030 with a per capita income of $16,000 (Chen, 2007; World Bank, 2013). The average per capita income in 2007 is tenfold compared to 1961, which leads

[2] Source: Piao et al. (2010).

Figure 1.2 Water resources per capita



to drastic changes with a more than fivefold increase in meat supply per capita (Kastner et al., 2012). The production of 1kg of pork requires 3.5kg of grain and production of 1kg of grain requires 800kg of water (Giordano, 2007). Meat consumption increased from 12.7kg in 1980 to 20.7 kg in 2012 (NBSC, 2013). Hence, the increase in meat production has led to a substantial increase in the demand for water.

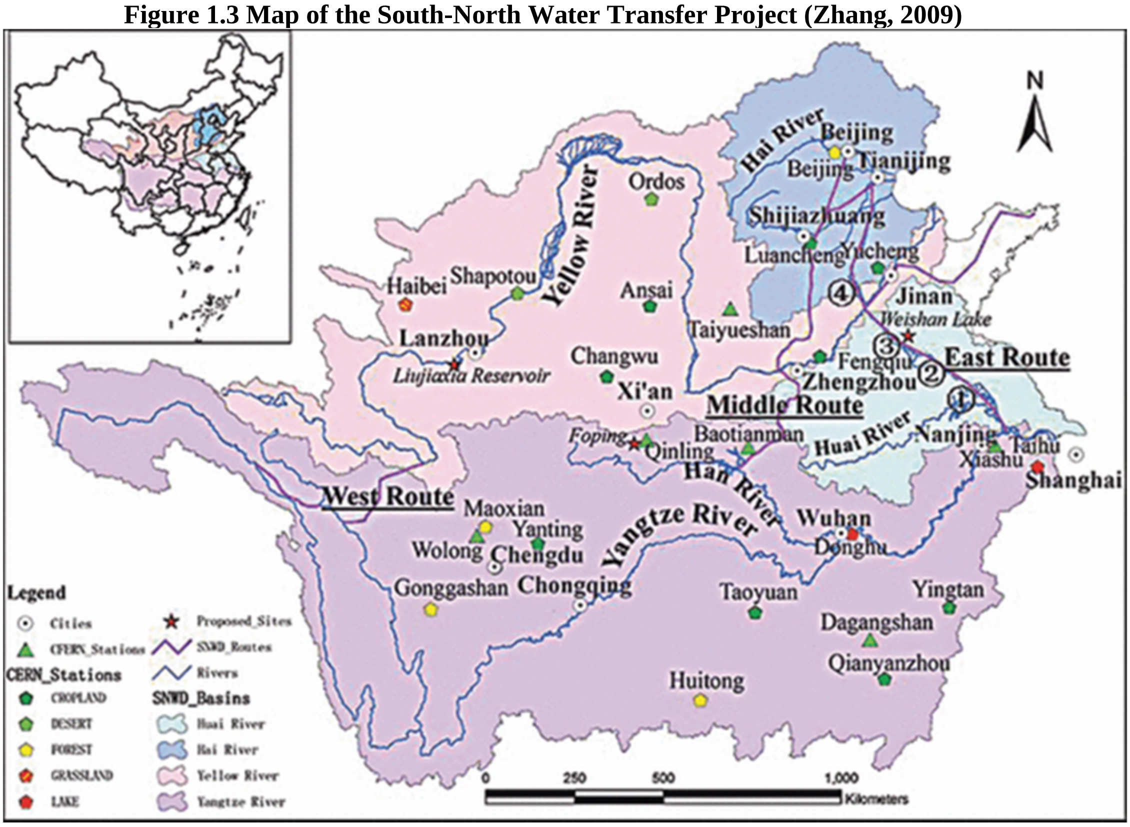
The surging demand for water has also been pushed up by rapid urbanization and industrialization. Urban resident consumed 72.3 m^3 for household use in 2010, which is more than twice the amount consumed by rural resident (29.9 m^3) (MWR, 2011). The level of urbanization is expected to rise to 60 percent in 2030, which will put further pressure on water resources (Chen, 2007). The demand for water from industry has increased from 45.7 km^3 in 1980 to 113.9 km^3 in 2000 and to 142.4 km^3 in 2012.

Thirdly, water availability has decreased due to water pollution and climate change. A volume of 685 billion tons of wastewater was generated in 2012 (NBSC, 2013), of which 80% was discharged untreated into rivers, lakes and the sea (Bao and Fang, 2012). Approximately 40% of China's rivers is severally polluted (water quality below Class IV) and is unfit for human contact (MWR, 2012a). This is even worse in the 3H river basins where two thirds of the river water is unfit for human contact. China's lakes are also severely polluted. MWR (2012a) reports that 70% of the monitored major lakes suffer from eutrophication.

Fourthly, a significant decrease in annual precipitation has been observed in most of northern China while there is an increase in southern China, leading to more frequent droughts in the North and floods in the South (Wang et al., 2012). Besides, an increase in frequency and intensity of extreme climate events has been observed (Piao et al., 2010).

Among the climatic disasters, drought has the most serious impacts on agricultural production in China. It is estimated that the annually drought affected area has more than doubled from 11.6 million ha in the 1950s to 25.1 million ha in the 2000s (Chen, 2014). Over the same period, the drought damaged area, which has a yield loss of at least 30%, has increased from 3.6 million ha to 14.6 million ha. As a result, annual drought-related grain loss reached 28.3 million tons and economic losses amount to about 33 billion Yuan in the past two decades (Ju et al., 2013). The grain loss accounts for approximately 5% of China’s total grain production.

Figure 1.3 Map of the South-North Water Transfer Project (Zhang, 2009)



The Chinese government is aware of and has responded to the water shortage problem in northern China. However, the strategies focus on augmenting water supply rather than controlling water demand (Xie et al., 2009). Among the water resource management strategies, the South-North Water Transfer Project (SNWTP) launched in 2002 is perhaps the best known. The SNWTP is the world’s largest water transfer project with three independent routes (East, West, and Middle) stretching more than 4,000 km (Zhang, 2009; see Figure 1.3). The east and middle route are under construction and the west route is being planned. Upon completion by 2050, the project is expected to transfer annually 45 km^3 water from central and southwest China to meet water demand in the water-stressed north (about 20% of its present consumption). Although the project will bring about $3 billion economic return annually, the rationality is still debated (Berkoff, 2003). The total investment will reach $62 billion, not to mention the social cost and environmental consequences. At least 300,000 residents along the central route will be resettled (Freeman, 2011). Zhang (2009) summarizes the various environmental consequences of the inter-basin water transfer: water quality degradation along the canal due to untreated industrial wastewater discharge, salinization in the receiving areas, invasion of alien species and river ecosystem change in the water supply areas[3]. If all these costs are also counted, the cost per m^3 of water from the SNWTP are estimated to be approximately 20 yuan (US$3), which is more than four times the cost of seawater desalination (5 yuan) (Shi and Feng, 2011).

1.2 Water scarcity in the Guanzhong Plain

The Guanzhong plain is located in Shaanxi province. It covers an area of 55,000km^2 and has a population of 23.5 million. It accounts for 25% of Shaanxi's total land area but is home to 65% of its population. In 2012, the Plain's GDP was 880 billion Yuan (approximately 37,500 Yuan per capita), of which 10% is from agricultural production. The 1.5 million ha arable land in the Plain accounts for 52% of the province's total. With an average annual growing season temperature ranging between 12°C and 13.6°C, the region has favorable conditions for grain and industrial crop production (Tang et al., 2013). The kinds of crops grown in this area include grain crops such as wheat, corn, cotton and cash crops such as vegetables, apples and kiwis. Wheat and corn are the main crops. They account for 45% and 30% of the total sown area, respectively. The two crops are rotated such that wheat grows in the October-June period and corn in the July-September period, after wheat harvest.

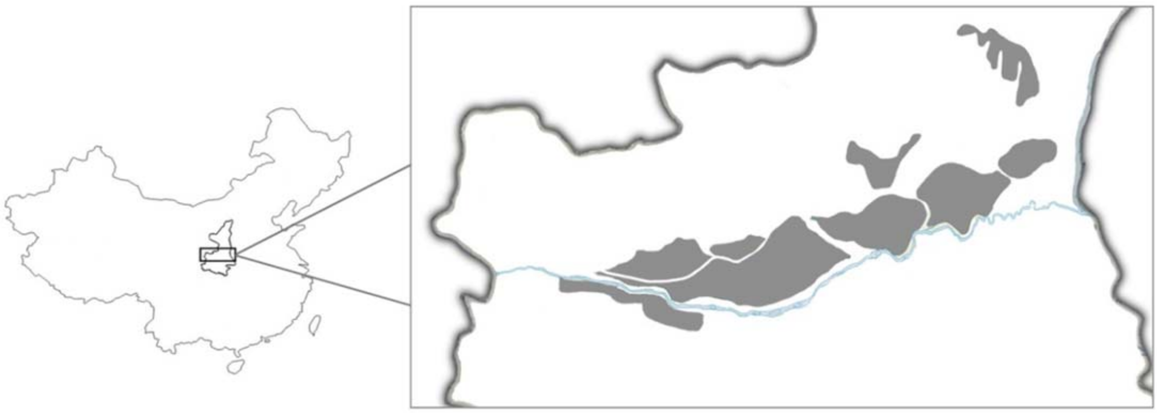
The Guanzhong Plain, which is located in the Yellow River basin, is a typical Chinese water scarce region (see Figure 1.4 for a map of the Plain). In 2011, annual water

[3] The Chinese government should pay special attention to the environmental consequences. Similar water transfer projects by the former Soviet Union became disasters and were abandoned because of environmental concerns (Micklin, 1988).

availability per capita was only 400 m^3, which is only 20% of the national average and is far below the extreme water scarcity threshold (SPBS, 2012). There are several reasons for this extreme scarcity. First, average annual precipitation is very low at 550mm. Secondly, the distribution of precipitation in the Plain is skewed. For instance, as much as 80% of total rainfall in 2011 was concentrated in the summer (July-September) while winter (December-February) received only 3%. Note that the season that crops require most water is March-May, which has only 15% of annual precipitation (SPBS, 2012). The probability of drought is very high at 70-80%. Thirdly, due to land erosion, water in the main river (Wei River) contains massive sand and soil, making it unsuitable as irrigation water due to the presence of toxics, transportation and distribution problems. In addition, it is technically not feasible to purify it so that it becomes suitable as irrigation water.

Because surface water is insufficient to meet increasing demand, underground water is abstracted at a large scale. The Plain withdraws 87 per cent of its surface water and 85 per cent of its renewable groundwater every year, which is far beyond the sustainable percentage of 25% (Yu et al., 2000). This has caused an annual decline of 2m of the groundwater table since 1980s (Li and Cao, 2003). For instance, the most seriously affected area is Xi'an city where the groundwater table has dropped 100 meters (SPDWR, 2012). Pollution is also a serious problem in the Plain with 700 million tons of waste water generated each year of which only 13% is treated before discharge.

Figure 1.4 Map of the Guanzhong Plain



1.3 Irrigation agriculture

Since the rain season June-September does not coincide with the growing season, irrigation plays a crucial role in ensuring agricultural production and food security in China. Approximately 52% of farmland is irrigated which is one of world's highest levels.

Approximately 75% of China's grain is produced on irrigated land. Because precipitation is insufficient, irrigated farmland has far larger crop yield than rain-fed farmland, especially in water-stressed areas (Jin and Young, 2001). For instance, in the North China Plain wheat yield of irrigated farmland is 56% higher than that of rain-fed farmland (Liu et al., 2007). Irrigation in China is also important from an international perspective. Brown and Halweil (1998) show that if China is facing ever-growing water deficits in agriculture, it cannot retain its high food security level and needs to import 200 million tons in 2030, which is equivalent to current total world grain exports. This in its turn will threaten the stability of the world's grain market (Jin and Young 2001).[4] Due to substantial contribution to its agricultural output, China has been expanding its irrigated farm land from 45 million hectares in 1978 to 63 million hectares in 2012 (NBSC, 2013). There exists some 90,000 reservoirs across China to provide water for irrigation districts.

Irrigation consumes 60% of China's total water withdrawal which has caused overexploitation of groundwater and, as a result, declining ground water tables (Fang et al., 2010). The number of tubewells in China has increased from 1.95 million in 1978 to 5.4 million in 2011 (MWR, 2012b), of which three quarters are located in the 3H river basin. Due to intensive exploitation, the area with groundwater table decline has reached 90,000 km^2, of which 70% is in the North China Plain (Liu and Yu, 2001).

The agricultural sector is facing a strong competition from other water users. Rural-to-urban migration and the growth of cities have led to a transfer of water from agriculture to industry and households. As a result, industrial and residential water use have gone up from 9% and 2% of total water use in 1980, respectively, to 24% and 13% in 2010 (Jin and Young 2001; MWR 2010). As a result, the percentage of water used by agriculture has decreased from 80% in the 1980s to 60% in 2012, threatening China's food security.

Despite its scarcity, irrigation water is wasted to a great extent because of weak water management. Particularly, irrigation water use efficiency, i.e. the amount of water actually absorbed by irrigated plants relative to the volume of water withdrawn, is extremely low at 40 per cent, compared to 80 per cent in developed countries like Israel,

[4] Surging Chinese demand will push up grain price worldwide which in its turn will stimulate production. However, the price increase is likely to negatively affect the welfare of low-income countries, especially in the short run. A well-known example is the global food price hike in 2010. Its main cause was that Russia temporary banned wheat export after suffering a severe drought in 2010. Low income countries like Pakistan were seriously affected (Welton, 2011). Note that the impacts from extreme climatic events in China may shock the world grain market to a large extent because the worldwide grain producers may not respond fast enough to meet a huge demand in case of a severe drought in China.

the US and Japan (Khan et al. 2009). Water productivity, measured as mean output per m^3 of water is 0.85kg which is 50 per cent of water productivity in developed countries (Khan et al. 2009). This is partly due to the low adoption rate of advanced water-saving techniques. 60% of the irrigated farmland is not equipped with any advanced techniques, such as lined-canal, low-pressure pipelines and drip irrigation equipment. Because of lack of lined canals, 45% of irrigation water never reaches the farmland and is wasted from canal leakages (MWR, 2007). Another reason is that the price charged for irrigation water in China is far below its value so that farmers have no incentives to conserve water (Yang et al. 2003; Lohmar et al. 2007). The main reason for keeping the price below its value is that increasing rural income is a primary policy goal of the Chinese government, since the income gap between rural and urban has been widening substantially over the past decades. There is a widespread belief among Chinese policy-makers, but also elsewhere in Chinese society, that a higher price for irrigation water is at odds with the objective of narrowing the income gap (Johansson et al. 2002; Tsur et al. 2004).

Irrigation plays an important role in Shaanxi and the Guanzhong Plain. It is organized by irrigation districts, which have been in operation for thousands of years. Among the 11 largest irrigation districts (each covering an area of more than 20,000 ha) in Shaanxi, ten are located in the Guanzhong Plain (Wang et al., 2006). Due to its flat topography and fertile land, the Plain has a well-structured irrigation infrastructure which irrigates an area of 0.78 million hectares of farmland accounting for 57 per cent of the irrigated land in Shaanxi Province. Approximately 75% of grain production comes from irrigated land which accounts for 50% of total arable land. Similar to other regions in Northern China, industry and households in the Plain have been competing with agriculture for water. The percentage of water used in agriculture has decreased from 80% in 1980 to 55% in 2011, while water used by industry has increased from 10% to 20% and by household from 10% to 25% (SPDWR, 2012).

Before 1978, (agricultural) land was collectively owned and the irrigation canals were managed collectively. Irrigation systems were managed by the village councils who were in charge of allocating irrigation water, canal maintenance and fee collection. In 1978 the collective farming system was reformed resulting in the Household Responsibility System which provided farmers with land user rights. The irrigation system, however, could not be de-collectivized and remained largely unchanged, since farmland was too fragmented. The irrigation canals remained under control of the village councils. Furthermore, user rights were not transferred which implied unclear canal maintenance responsibilities and insufficient incentives to invest in improving and maintaining the infrastructure (Lohmar et al. 2003).

1.4 Overall objective and sub-objectives

1.4.1 Overall objective

China has limited water resources. Moreover, water is not at the right place at the right time. In addition, the demand for water is growing rapidly due to population surge, increasing income, urbanization and industrialization. Water availability is further worsened by water pollution and climate change. National supply-oriented water policy and management are costly and unable to solve the water scarcity problem. At the same large amounts of water are wasted or polluted. Therefore, a demand-oriented strategy is also needed. The main objective of this dissertation is to address one aspect of a demand oriented strategy, viz. irrigation water use efficiency in the Guanzhong Plain which is facing severe and increasing water scarcity problems. Efficient use of irrigation water use in the Plain is important because agriculture is the largest water user. Moreover, it is facing increasing competition for water from industry and the residential sector which have higher potential marginal returns to water (SPDWR, 2012). Hence, improving irrigation water use efficiency is not only of interest and important to farmers but to virtually all economic sectors.

1.4.2 Sub-objectives

From the above overall objective I derive the following sub-objectives.

(i) Analysis of the impacts of management reform on technical efficiency of irrigation water use

The first sub-objective derived from the overall objective is the analysis of the impacts of irrigation management reforms on irrigation water use efficiency. The irrigation infrastructure rapidly deteriorated under this management system, causing massive waste due to seepage. Since 1998, the management authority for irrigation systems was transferred from government agencies to farmers or other local, nongovernmental organizations. Various types of irrigation management reforms have taken place since 1998 whose aim is to increase water use efficiency (Wang et al. 2006). In 2005, 80 per cent of the total number of 6,000 canals was operating under reformed management.

Under the new system the state remained the owner of the water while water user rights were introduced which directly or via collectives were allocated to individual farmers. Particularly, private companies (COM), Joint-stock co-operatives (JSC) and water user associations (WUA) have been introduced as the main types of management organizations. COM is a private company that purchases water from the irrigation district and sells it to farmers. It is allowed to make a profit from selling water but is also responsible for possible losses and maintenance of the canals. A JSC is a company owned by stakeholders, which may include farmers, management staff and local village and town cadres. The shareholders jointly invest in water supply, canal maintenance and water fee collection. Finally, a WUA is a non-profit and democratic organization whose main objective is to allocate irrigation water among its members.

The research question following from this sub-objective is: to what extent has irrigation management reform improved water use efficiency? Which management type is most efficient?

(ii) Awareness and Perception of irrigation water scarcity

The second sub-objective relates to farmers' awareness and perception of water scarcity as key determinants of future irrigation water use. Perception of water scarcity is defined as the recognition of the state of water scarcity, whereas awareness refers to the attention (mindful and heedful) to water scarcity. Perception and awareness are hypothesized to interact. First of all, perception is a basic determinant of awareness because awareness is the synthesis of the information triggered and transmitted by perception. There is also a reverse effect in that awareness helps to recall past experiences and lowers the threshold of perceiving the stimuli. Standard economic models, including efficiency models assume that producers conclude economic decisions based on profit maximization but tend to neglect psychological and sociological factors. If awareness and perception influence irrigation water use, insight into their impacts is a prerequisite for the development of adequate and effective policy handles. Particularly, the more clearly water scarcity is perceived as a problem, the more likely farmers will respond to stimuli to adopt water-saving practices and technologies[5].

[5] Of course, adoption of water saving techniques and practices could also be achieved via demand and control policy. However, demand and control policies tend to be less effective and efficient. See amongst others Barde (2000).

The research questions derived from this objective is: How are farmers' awareness and perception of water scarcity formed? What are the influencing factors for the formation?

(iii) The impacts of perception on technical and allocative efficiency of irrigation water use

The next sub-objective is to get insight into the impacts of psychological factors on farmers' water use efficiency. As argued by Folmer (2009) and Folmer and Stenman (2011), when psychological factors are determinants (in the present study of efficiency), ignoring them leads to model under-specification, and thus to biased estimators of the coefficients of the standard explanatory variables of efficiency, like farm and farmer characteristics, and to invalid inference. Furthermore, if perception turns out to be a determinant of efficiency, it is a potential policy handle in that improving perception e.g. via extension, may induce farmers to reduce their water use.

The impacts of perception on both technical and allocative single factor efficiency of irrigation water is considered. The first concept refers to the ratio between actual water use and the minimum feasible use of water, keeping other inputs and output constant. Single-factor allocative efficiency is the ratio between the cost when the single-factor is technically efficient and the optimized cost when all inputs are technically and allocatively efficient. Allocative efficiency analysis is needed because technical efficiency analysis does not measure a farmer's ability to allocate irrigation water and other inputs to their cost-minimizing input proportions.

Since the analysis of the present sub-objective also gives insight into the impacts of conventional determinants of technical and allocative efficiency, it offers insight into the efficacy of water pricing as a policy handle. In China, the use of this policy instrument is still under debate. Huang et al. (2010) argues that the price of irrigation water in China is too low to induce farmers to save water. However, policymakers fear that higher prices will jeopardize farmers' income and further widen the gap between rural and urban residents (Lohmar et al., 2007). Specifically, we test whether income loss due to higher irrigation water price can be offset by more efficient use of water.

The research questions derived from this objective is: Does farmers' awareness of water scarcity effect their single factor technical and allocative irrigation water use efficiency? Could income loss due to increasing water price be offset by increasing water use efficiency?

(iv) Adoption of irrigation techniques

Efficiency of irrigation water use to a large extent depends on the irrigation techniques applied. Therefore, as the next sub-objective we analyze the types of irrigation techniques that have been adopted and the determinants of adoption. The conventional factors supposed to affect adoption of agricultural techniques include farm and farmer characteristics, availability of credit, information and labor availability (Feder et al., 1985). These factors have also been analyzed in relation to the adoption of irrigation techniques (Zhou et al., 2008; Abdulai et al. 2011; amongst others). In addition, production risk has been found to be an important determinant of adoption of agricultural techniques in general (Feder et al., 1985; Foster and Rosenzweig, 2010; Liu, 2013; among others). However, despite the evidence, production risk is frequently ignored in agricultural adoption studies in developing countries like China, because of measurement problems (Liu and Huang, 2013; Just et al., 2010).

The need to consider production risk in adoption studies of agricultural techniques - including irrigation techniques- relating to northern China has increased because precipitation has begun to vary more and more across years because of climate change. Consequently, farmers are facing more and larger unexpected hazards of extreme weather (e.g. extremely low precipitation) which has increased production risk. Hence, a farmer may consider and choose to adopt water-saving techniques to reduce weather related risk. Meanwhile, attitude towards risk also plays a role in adoption behavior (De Pinto et al., 2013). Since it usually comes with a cost and is accompanied by uncertainty and risk, a risk-averse farmer may be skeptical about adoption, even if there is a production risk. The opposite is likely to hold for a risk-loving farmer.

Hence, the research question derived from this sub-objective are: What kinds of irrigation techniques have been adopted? What are the impacts of demographic and socio-economic factors, farm characteristics, production risk and farmer attitudes towards risk on the adoption?

(v) Estimation of the impacts of the determinants of technical and allocative efficiency: Seemingly Unrelated Regressions (SUR) or Structural Equations Modeling (SEM)?

Sub-objective (iii) focuses on the determinants of perception on technical and allocative efficiency. The latter two concepts both relate to a farmer' ability to use water efficiently.

From the definitions, it follows that efficiency is a psychological trait (ability) and thus inherently unobservable. That is, it is a theoretical construct or latent variable. Hence, it can be only measured indirectly via observed indicators, though with measurement error (Folmer and Oud, 2008; Oud and Folmer, 2008).

The first research question derived from the present sub-objective is: can efficiency be taken as a latent variable with technical and allocative efficiency as indicators? If so, which one is the most reliable indicator?

A related sub-objective is methodological in that the performance of Structural Equations Modeling (SEM) is compared to alternative (conventional) estimation procedures that do not treat efficiency as a latent variable but directly estimate the impacts of their determinants on the indicators instead. A typical example of the latter in the case of two or more indicators is Seemingly Unrelated Regression (SUR) which accounts for possible common factors that influence the error terms in the different equations.

The research question derived from this objective is: how do SUR and SEM compare as estimators of the impacts of their determinants on allocative and technical efficiency?

1.5 Thesis outline

The organization of this dissertation is as follows.

Chapter 2 examines the efficiency of the 1998 irrigation management reform in the Guanzhong Plain, Shaanxi Province, China, at farm and canal level. The basic characteristics and mechanism of the three types of reforms, e.g. private companies, joint-stock co-operatives, and water user associations, are introduced and compared. It also discusses the expected improvements of effectiveness of the three reforms from the following three perspective: better irrigation infrastructure, timely water delivery and more farmer participation. Next it summarizes the development of the management systems for the period 2000–2005. This is followed by a detailed description of the definition of irrigation water technical efficiency and its measurement. A fixed effects stochastic frontier analysis is applied to estimate irrigation water use efficiency, based on panel data for 800 farmers, spread over 80 irrigation canals, for the period 1999–2005. In a second-stage analysis, single-factor technical efficiency obtained by means of the stochastic frontier analysis is regressed on the management systems, together with other explanatory variables, such as water availability, water price and disclosure, to get insight into the sources of variation in irrigation water use efficiency.

In chapter 3, the formation of awareness and perception of water scarcity is analyzed. A conceptual model of awareness and perception of irrigation water scarcity (i.e. the main variables and their relationships) is developed. Since both awareness and perception are latent (unobserved) variables, sets of indicators to measure the two variables are developed. A structural equation model (SEM) is developed and estimated, based on a dataset of 446 farmers in the Guanzhong Plain. The effects of farmers' characteristics (age, education, experience, social network, media access and time spent on farming), and water price, on awareness and perception are investigated.

Chapter 4 extends the previous analysis of water use efficiency by estimating both single-factor technical and allocative efficiency of irrigation water. The two efficiency measures are estimated by simultaneously estimating a production function, and its corresponding first-order conditions for cost minimization, based on a sample of 347 wheat growers in the Guanzhong Plain. A second-stage analysis is conducted to explain the variances of the water use efficiency measures obtained from the first stage. It is assumed that farmers who clearly perceive water as a scarce input are likely to be intrinsically motivated to be efficient. We also hypothesize that efficient farmers perceive water scarcity less as a problem. Other factors such as farm-specific characteristics and socio-economic features are also considered as determinants. Age, time spent on farming, land fragmentation, irrigation infrastructure and income are assumed to impact water use efficiency while income, education, water price and precipitation are linked to perception of water scarcity.

Chapter 5 analyzes adoption of irrigation technologies. First, an overview of irrigation techniques applied in the study area is presented. Next, we develop and estimate an adoption model consisting of the following sequential stages: (1) awareness of water scarcity, (2) awareness of water saving techniques, and (3) intensity or extent of adoption. The first stage is defined as a farmer's attention to, and concern about, water scarcity and its possible negative impacts on production. For the second stage, awareness of water saving techniques is taken as the number of water-saving technologies the respondent knows of. The third stage is defined as the number of household-based measures adopted. Each stage is considered to be a necessary condition for the next stage which implies that promotion of irrigation water saving via adoption of efficient techniques requires thorough understanding of all three stages. Based on a cross-sectional data set of 360 farmers, a production function consisting of an average production function and a risk function is simultaneously estimated to obtain production risk and farmers' attitude towards risk. The two risk variables, together with the other explanatory variables, are used to estimate the three-stage adoption model. Similar to chapter 3, awareness of water scarcity is linked to age, education, time spent on farming, water price, social network, and media access. This model is estimated by ordinary least squares. For the second stage model, awareness of water scarcity is regressed on age, education, time spent on farming, water price, social network, and media access, production risk and farmers' attitude towards risk (Poisson model). For the third-stage model, the variables used at stage two, together with financial status, are used to explain intensity of adoption.

Chapter 6 discusses the option to take water use efficiency as a latent variable with technical and allocative efficiency as indicators. The indicators are adopted from chapter 4. We compare estimation of the coefficients of the explanatory variables by means of structural equation modeling (SEM) and seemingly unrelated regression (SUR). SEM takes the efficiency measures as indicators of the underlying latent variable efficiency while SUR takes them as separate dependent variables, but accounts for possible common factors that influence the error terms in the different equations. The signs, significance levels, and magnitudes of the coefficients of both models are compared.

Chapter 7 summarizes the preceding chapters and presents the main conclusions. It also discusses some directions for further research.

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Chapter 2

The impacts of management reform on irrigation water use efficiency in the Guanzhong Plain, China[6]

Abstract: This paper examines the efficiency of the 1998 irrigation management reform in the Guanzhong Plain, Shaanxi, China, at farm and canal level. Stochastic frontier analysis is applied to estimate irrigation water use efficiency, based on panel data for 800 farmers, spread over 80 irrigation canals, for the period 1999-2005. Analysis of determinants of water use efficiency shows that at farm level, water price and disclosure are important factors. Compared to the base case of unreformed, management reform has a positive impact with water user association having the largest effect, followed by joint-stock cooperative and private company. The canal model is in line with the farm level model, although estimates are less significant.

JEL classification: Q15 Q25 Q12 D24

Key words: Irrigation water technical efficiency, Stochastic frontier analysis, Water user association, Joint-stock cooperative, Private company

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2.1 Introduction

China has been increasingly facing water scarcity. National annual renewable water availability *per capita* was 2,100 m^3 in 2010, close to the threshold of 2,000 m^3 below which there is water stress[7]. China's water supply cannot meet its growing demand. Currently, there is a deficiency of approximately 40 billion m^3 per year (MWR 2007). Of China's 662 cities, 300 suffer insufficient water supply and 110 severe water shortages (Li 2006). Liu and He (2000) predicts that water use in China will rise by 60 percent to 832,000 million m^3 per year in 2050 such that water deficit could reach 400 billion m^3 (roughly 80% of current availability; Tso 2004).

China's spatial water distribution is highly skewed. The North has 65 percent of arable land while it is endowed with only 18 percent of China's total water resources. The three major basins in China, i.e the Huang, the Huai and the Hai river basin, contain 40 percent of arable land, produce over 60 percent of the nation's wheat and 40 percent of its corn, but have less than 8 percent of the national water resource. Available water volumes in these three basins are 672, 483 and 314 m^3 *per capita*, respectively, far below the water scarcity threshold of 1,000 (Jiang 2009). In Northern China, precipitation is one fourth of the South's. In addition, 80 percent of annual precipitation in the North is concentrated in the summer months June-September causing serious flooding during those months and draughts for the rest of the year. To meet its demand, Northern China withdraws 59 percent of its surface water resource and 52 percent of its ground water resource every year, which indicates severe water scarcity[8]. Over-exploration has thus caused negative replenishment and groundwater depletion (Jiang 2009). In the Yellow river, the second longest river in China, river discharge to the sea was 51 percent less in 2000 than in 1950 (Wang et al. 2006c). Moreover, the number of areas with overexploitation of groundwater increased from 56 in the early 1980s to 164 in 2007, covering an area of 180,000 km^2 (MWR 2007).

In recent years, water scarcity has been worsening because of climate change and water pollution. Climate change has led to an increase of serious droughts in the northwestern parts of the country and of devastating floods in the southwest. In the

[7] The UNDP, UNEP, World Bank and the World Resources Institute define "water stress" as annual water availability between 1000 and 2000 m^3/person, and "water scarcity" when availability is below 1000 m^3/person (Shalizi 2006).
[8] Raskin et al. (1997) argues that a region is water scarce, if annual withdrawal is between 20% and 40% of its available water resources, and severe water scarce, if the figure exceeds 40%.

Yellow River basin, average temperatures have increased while precipitation and river runoff have decreased in the past 50 years (Fu et al. 2004). Degraded water quality due to pollution has further reduced water availability by 10 per cent (Jiang 2009).

Irrigation plays an important role in ensuring food security for China's large and still growing population. About 75 per cent of China's grain production comes from irrigated land which accounts for 40 per cent of China's total arable land (Khan et al. 2009). The main grain-producing region is Northern China. However, as mentioned above, its natural rainfall is far below its water needs for agricultural production. In addition, the rain season June-September does not coincide with the growing season (Deng et al. 2006). Hence, extensive irrigation is needed.[9]

China is going through a large number of rapid, profound socioeconomic changes with far-reaching environmental ramifications including an increase in water use. Its large population of 1.37 billion in 2011 will increase to 1.6 billion in 2030 which will lead to a substantial increase in the total demand for food and thus for water (Chen 2007). However, not only will the total demand for food increase, but also its composition. China is experiencing large-scale dietary shifts from grain to meat and fruit, again with a substantial increase in the demand for water (Giordano 2007).

Another major development with consequences for water use is accelerating industrialization and urbanization. Cultivated farmland has been shrinking since the 1990s with more than half of the reduced area allocated to urban expansion and industrial development (Chen 2007). Rural-to-urban migration and the growth of cities have led to a transfer of water from agriculture to industry and households. As a result, industrial and residential water use have gone up from 9 per cent and 2 per cent of total water use in 1980, respectively, to 24 per cent and 13 per cent in 2010 (Jin and Young 2001; MWR 2010). China's urbanization level is expected to reach 60 per cent by 2030 placing further pressure on future water demand (Chen 2007).

The above developments have seriously endangered the sustainability of water use and food production. Brown and Halweil (1998) show that if China is facing ever-growing water deficits in agriculture, it cannot retain its high food security level and needs to import 200 million tons in 2030, equivalent to current total world grain exports. Thus,

[9] Irrigation tends to double productivity and yield compared to non-irrigation (Jin and Young 2001).

China's grain production and water availability may threaten the stability of world's grain market (Jin and Young 2001).

Since 80 per cent of its food is produced on irrigated farmland, efficiency of irrigation water use plays a crucial role in feeding China's large and still growing population (Yang et al. 2003). However, irrigation water use efficiency, i.e. the amount of water actually absorbed by irrigated plants relative to the volume of water withdrawn, is extremely low at 40 per cent, compared to 80 per cent in developed countries like Israel, the U.S. and Japan. Water productivity, measured as mean output per cubic meter of water, is 0.85kg which is 50 per cent of water productivity in developed countries (Khan et al. 2009).

Traditionally, irrigation systems were managed by the village leadership councils who were in charge of allocating irrigation water, canal maintenance and fee collection (Huang et al. 2009). In 1978 the collective farming system was reformed to provide farmers with user rights. However, the irrigation system remained largely unchanged. Particularly, the irrigation canals remained under control of the village leadership councils and user rights were not transferred which implied unclear canal maintenance responsibilities and insufficient incentives to invest in improving and maintaining the infrastructure (Lohmar et al. 2003). Farmers were neither driven by economic interests to apply water-saving technologies, nor to maintain canals to improve efficiency of water use. Consequently, large quantities of water were wasted due to seepage.

Since the 1980s, more than 25 countries in Asia, Africa, and Latin America have turned over the management authority for irrigation systems from government agencies to farmers or other local, nongovernmental organizations (Vermillion 1997). This has also happened in China where various types of irrigation management reforms have taken place since 1998 (Wang et al. 2005). Private companies (*COM*), Joint-stock cooperative (*JSC*) and Water User Association (*WUA*) were introduced as the main types of management organizations. The core objective of the reform was to increase water use efficiency. *COM* is a private company that purchases water from the Irrigation District and sells it to farmers. It is allowed to make a profit from selling water but is also responsible for possible losses and maintenance of the canals. A *JSC* is a company owned by stakeholders, which may include farmers, management staff and local village and town cadres. The shareholders jointly invest in water supply, canal maintenance and water fee collection. Finally, a *WUA* is a non-profit and democratic organization whose main objective is to allocate irrigation water among its members.

Few studies have been undertaken to analyze the impacts, including effectiveness, of the reforms in China. As one of the few exceptions, Wang et al. (2006b) found that not every reform succeeded in reducing water use. They conclude that clear incentives are required for managers and farmers to save water. Wang et al. (2010) found that *WUA* reduced water use substantially. However, the definitions of water use efficiency used by Wang et al. (2006b, 2010) as water use per hectare and yield per m^3 water, respectively, are inaccurate in that they do not take into account that yield is not only produced by water but also by other inputs. In addition, they did not address the issues to what extent the irrigation reforms improved water use efficiency, and which types of reforms were the most successful. The present paper intends to (partly) fill this gap for Shaanxi Province in northwest China, which is a major food-producing region. First, it analyzes the efficiency of irrigation water use at farm and canal level. Secondly, it identifies the main determinants of efficiency with special attention to the performance of *COM*, *JSC* and *WUA* as the main types of irrigation management reform. The analysis is at both micro (farm) and regional (canal) level. It thus is rather unique, since it offers an opportunity to compare the correspondence of regional forces to the underlying micro-scale forces[10].

The paper is organized as follows. In section 2.2, a description of the study area and its irrigation management systems is presented. The methodological framework, stochastic frontier analysis, is briefly discussed in section 2.3. The sample design and data follow come up in section 2.4 while the main empirical results are presented in section 2.5. Conclusions and policy recommendations follow in section 2.6.

2.2 Study area and the irrigation management systems

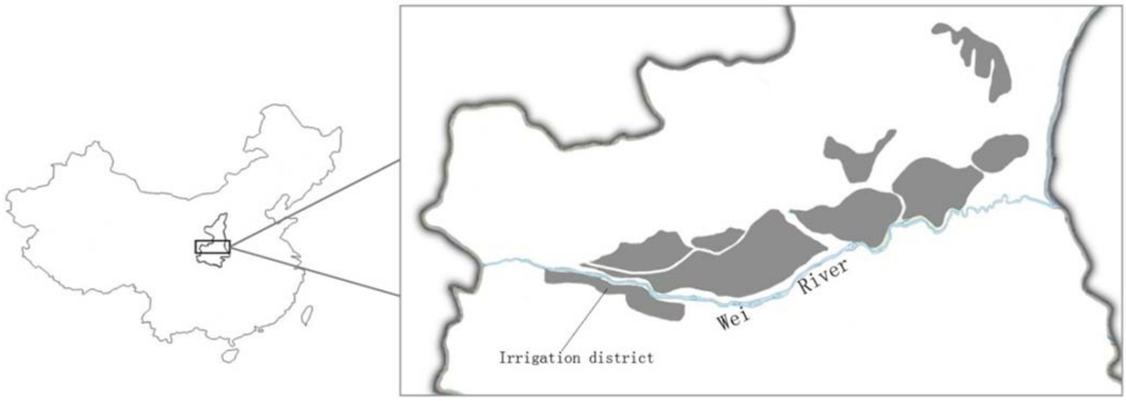
2.2.1 Study area

This study was conducted in the main irrigation districts in Shaanxi Province which is one of the provinces with severe water shortage in Northwestern China. The irrigation districts, which are located in the arid and semi-arid regions in Shaanxi, account for 70 per cent of Shaanxi's total land area. However, they are endowed with only 30 per cent of the province's water resources. Thus, irrigation water is essential to Shaanxi's agricultural production.

[10] For another micro-regional analysis, see Tveteras and Battese (2006).

Irrigation in Shaanxi is organized by irrigation districts, which have been operational for thousands of years. Among the eleven largest irrigation districts (each covering an area of more than 20,000 ha), ten are located in the Guanzhong Plain (See Figure 2.1 for a map of the Guanzhong Plain with the nine irrigation districts included in the survey). Due to its flat topography and fertile land, this plain has a well-structured irrigation infrastructure which irrigates an area of 0.78 million hectares of farmland accounting for 57 per cent of the irrigated land in Shaanxi Province. The Guanzhong Plain has a semi-arid climate, with annual precipitation of 480-816 mm. With an average annual growing season temperature ranging between 12℃ and 13.6℃, the region has favorable conditions for grain and industrial crop production. Total grain yield (3.6 million tons) is 37 per cent of the province's output. The main crops are wheat and corn. Cash crops include amongst others apples, pears, kiwis and cotton. The 5.52-million population in the 9 irrigation districts accounts for 20 per cent of total provincial agricultural population.

Figure 2.1 Map of the study area and irrigation districts



Rivers and reservoirs are the main irrigation sources in the Guanzhong Plain. Each irrigation district has its own water sources and set of canals. The Irrigation Management Bureau bears the ultimate responsibility for water distribution, maintenance and operation of the main canals in each district. Water is collected in the rainy seasons. During the irrigation seasons, water flows from the main canal to sub-canals and then to the village canals. An irrigation manager is responsible for coordinating water deliveries from the sub-canal to the farmlands.

2.2.2 The irrigation management system

Before 1978, (agricultural) land was collectively owned and the irrigation canals were managed collectively. In 1978, farmland was de-collectivized and the Household Responsibility System was introduced. The irrigation system, however, could not be de-collectivized, since farmland was too fragmented. As explained in the Introduction, the irrigation infrastructure rapidly deteriorated under this management system, thus endangering the sustainability of agriculture production.

In 1997, the irrigation management systems in the main irrigation districts in Shaanxi were partly de-collectivized (Wang et al. 2006a). A World Bank pilot water management program under provincial government support was initialized to encourage management reform. In 2005, 80 per cent of the total number of 6,000 canals was operating under reformed management. Under the new system the state remained the owner of the water while water user rights were introduced which directly or via collectives were allocated to individual farmers. Based on both Chinese and international experiences (Svendsen et al. 1997; Wang et al. 2006a; Wang et al. 2010), the reform was targeted at improving farmers' water use efficiency in three ways: better irrigation infrastructure, timely water delivery and more farmer participation. Better infrastructure was expected to reduce water losses in the process of delivering water to farmland. Farmer participation was assumed to result in increased farmer control over water availability and water use, reduction of conflicts and improved maintenance. Under collective (*Unreformed*) management, delayed delivery used to be common practice causing substantial reduction of yields (Wang et al. 2006b). The reform was expected to improve delivery[11].

As in other parts of China, in the Guanzhong Plain there are three different irrigation water allocation systems (management forms), (i) Private Companies (*COM*), (ii) Joint-stock Cooperatives (*JSC*) and (iii) Water User Associations (*WUA*). These three allocation models share the common goals of improving irrigation water management and enhancing water saving. The basic characteristics of the management models are the following (Wang et al. 2006a).

2.2.2.1 Private company (COM)

Via contracting, lease or auctioning, irrigation management is turned over from local officials to a private company (Lohmar et al. 2007). The company contracts with a committee that includes the Irrigation Management Bureau and village leaders. It determines the price farmers have to pay, though up to a maximum fixed by the Irrigation Management Bureau. The incentive of making profits induces the company to maintain infrastructure and to deliver water on time. Farmers pay for the water flow from the sluice

[11] Timely delivery is often taken as an indicator of irrigation performance (Meinzen-Dick 1995).

gate to their farmland. The waste incurred during transportation or because of mismanagement is the company's responsibility, so it has an incentive to save water via improving infrastructure and management techniques. The disadvantage of *COM*, however, is absence of stakeholder involvement, notably, farmer participation (Huang et al. 2009). Wang et al. (2006a) points out that a *COM*'s interest in improving irrigation infrastructure and management is limited because its main objective is making a short run profit.

2.2.2.2 Joint-stock Cooperative (JSC)

Profits are distributed among the stakeholders but they also incur possible losses. Basic *JSC* decisions like appointing general managers and approval of canal maintenance budgets are concluded collectively while daily activities, such as coordination of water delivery and water fee collection, are carried out by the general management. Another difference between a *COM* and a *JSC,* besides stakeholder involvement, is that the former can only manage one or several sub-canals while the latter can manage several main or sub-canals. A *JSC* can thus manage irrigation of a far larger area of farmland than a *COM* (Wang et al. 2006a). Finally, because of the variety of stakeholders involved, a *JSC* outperforms a *COM* in that it can obtain funding from several sources to invest in irrigation infrastructure. A *COM* is limited in this regard.

2.2.2.3 Water User Association (WUA)

Farmers, who share the same canal, can form a *WUA* (World Bank 1993). The role of a *WUA* is, however, not limited to typical irrigation management tasks; it may also facilitate the interaction and exchange of information among its members on water use techniques and related farming matters. *WUAs* are officially advocated by the Chinese government. The board is elected by the water users. Through regular *WUA* meetings, farmers are involved in decisions on various kinds of irrigation issues such as improving irrigation services, coordinating deliveries and reducing conflicts (Wang et al. 2006a). Under a *WUA*, farmers make irrigation schedules themselves, and control water delivery. Lohmar et al. (2007) argues that farmers organized in a *WUA* have a high willingness to invest in irrigation infrastructure and irrigation services. In practice, however, *WUAs* are not without limitations. In most *WUA*s, the role of the farmers in decision-making is limited because the village leaders or their representatives dominate the board. This is enhanced by the fact that educated farmers tend to become migrant workers in the cities, leaving agriculture practices to women. Due to lack of management experience, poor knowledge of irrigation techniques and limited interest due to small farm size, large groups of farmers are rather indifferent about joining a *WUA* (Wang et al. 2006a).

Table 2.1 shows the development of the management systems for the period 2000-2005. During this period the number of *Unreformed* dropped from 25 (31.25%) in 2000 to 9 (11.25%) in 2005. *COM* is the most prevalent system with a proportion ranging between 60% to 65% during the survey period. In 2000 there was only 1 WUA (1.25%), but the number gradually increased to 7 in 2005 (8%). A similar trend holds for *JSC*, although the initial (7.5%) and final numbers (17.5%) are substantially higher.

Table 2.1 Number and percentage of canals by management form from 2000 to 2005

Type	2000	2001	2002	2003	2004	2005
COM	48(60%)	50(62.5%)	50(62.5%)	52(65%)	52(65%)	50(62.5%)
JSC	6(7.5%)	12(15%)	14(17.5%)	14(17.5%)	14(17.5%)	14(17.5%)
WUA	1(1.25%)	1(1.25%)	5(6.25%)	5(6.25%)	6(7.5%)	7(8.75%)
Unreformed	25(31.25%)	17(21.25%)	11(13.75%)	9(11.25%)	8(10%)	9(11.25%)
Total	80(100%)	80(100%)	80(100%)	80(100%)	80(100%)	80(100%)

Source: The survey.

Table 2.2 shows the changes in the management system between 2000 and 2005. Out of the 25 non-reformed canals, 6 shifted to *COM*, 7 to *JSC* and 5 to *WUA*. The 6 canals under JSC in 2000 did not change management system during the period of investigation. Similarly for the canals under WUA and for 44 out of 48 canals under *COM*. Hence, once a canal is reformed, it tends to remain reformed. Nevertheless, 2 canals under *COM* in 2000 shifted back to *Unreformed* in 2005 indicating that not all reforms were successful.

Table 2.2 Changes in the number of management forms between 2000 and 2005

Type of management in 2000	Total	Type of management in 2005			
		COM	*JSC*	*WUA*	*Unreformed*
COM	48	44	1	1	2
JSC	6		6		
WUA	1			1	
Unreformed	25	6	7	5	7
Total	80	50	14	7	9

Source: The survey.

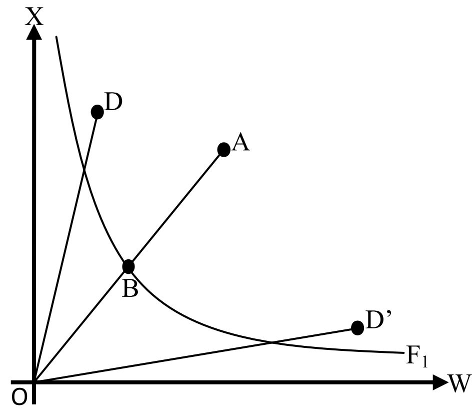
2.3 Methodological framework

2.3.1 Multiple-factor efficiency and its measurement

Efficiency is a measure used to assess economic performance. In the present case, efficiency relates to farm output as a function of a given set of inputs. Three types of efficiency are usually distinguished: technical, allocative and economic efficiency (Farrell, 1957). For the present paper, which focuses on efficiency of water use, technical efficiency suffices.

Following Farrell's (1957) pioneering work, the concept of technical efficiency is illustrated in Figure 2.2, with two inputs, i.e. irrigation water *W*, and *X* which denotes all other inputs including capital, labor and fertilizers, and a single output, *Y*. F_1 in Figure 2.2 is an isoquant which represents the production frontier at which a technically efficient firm uses least inputs to produce a given output. Point *B* is on the frontier indicating that the farm is technically efficient at this point. If a farmer produces beyond the frontier, for instance, at point *A*, he produces the same output as at point *B* but uses additional inputs in comparison with point *B*. Thus, the farmer is technically inefficient at point *A*. *Multiple-factor technical efficiency* (*MFTE*) at *A* is defined as *OB/OA*. Multiple-factor technical efficiency represents the minimum feasible input that can produce a given amount of output.

Figure 2.2 Multiple-factor technical efficiency

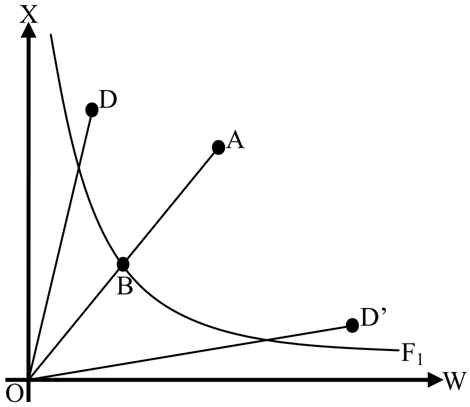


Note: Figure 2.2 is based on Farrell (1957), Kopp (1981) and Reinhard (1999).

2.3.2 Single-factor technical efficiency

Inefficiency can be caused by misuse of one or more factors and each factor may contribute a different magnitude to inefficiency. Because multiple-factor technical efficiency measures relate to inefficiency of all factors simultaneously, it does not reveal which factor(s) is (are) responsible for inefficiency and to what extent. Hence, it cannot identify the inefficiency of an individual factor. For instance, parsimonious use of irrigation water and inefficient use of other inputs (point *D* in Figure 2.2) may yield the same level of *MFTE* as excessive use of irrigation water and thrifty use of other inputs (point *D'* in Figure 2.2). However, we can get insight into the inefficiency caused by a single factor by way of single-factor technical efficiency analysis using the notion of *single-factor technical efficiency* (*SFTE*), as introduced by Kopp (1981, 1982). Below we refer to *SFTE* for irrigation water as *IWTE*.

Figure 2.3 Single-factor technical efficiency



Note: Figure 2.3 is based on Farrell (1957), Kopp (1981) and Reinhard (1999).

The concept of *SFTE/IWTE* is illustrated in Figure 2.3. *A*, *B*, *W*, *X* and F_1 are defined as in Figure 2.2. Point E^*, which is on the frontier, corresponds to a technically efficient producer who produces the same level of output as *A*, though with less input o per centf water. Compared to *A*, E^* uses less water (EE^*). Meanwhile, EE^* is the minimum feasible use of *W* conditional on a given level of input *X* (*OE*) and actual output. *SFTE* of *W* at point *A* thus equals EE^*/EA.

2.3.3 Estimation of the production function and the multi-factor inefficiency model with panel data

Having introduced the concept of *SFTE* in the previous section, we now turn to the methodology of measuring those concepts. Efficiency measurement is usually divided into two basic approaches, namely Stochastic Frontier Analysis (*SFA*) and Data Envelope Analysis (*DEA*). The first is based on econometric methods and the latter on linear programming. The main advantage of *DEA* is that it neither requires the specification of the functional form of the technology, nor of a particular distributional form for the one-sided inefficiency term.[12] Both are typical requirements of *SFA*. However, the *DEA* method is restricted in that it is highly sensitive to outliers. The stochastic frontier approach (*SFA*) on the other hand is less sensitive to outliers. We use *SFA* which was initially proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977), since it is more appropriate than *DEA* in agricultural research where the data is likely to be

[12] For application of *DEA* and *SFA* in regional efficiency analysis, see Suzuki et al. (2011) and Nakamura (2012), respectively.

influenced by measurement errors and the effects of weather conditions and natural diseases (Bravo-Ureta et al. 2007).

The general stochastic production function and the multi-factor inefficiency model for panel data are (Wang and Ho, 2010):

$$Y_{it} = F(X_{it}; \beta) \exp(\alpha_i + v_{it} - u_{it}), \quad (1)$$

$$u_{it} = f(Z_{it}\delta) * \varepsilon, \qquad i = 1, \dots\dots, N, \;\; t = 1, \dots\dots, T. \quad (2)$$

Production function $F(X_{it}; \beta)$ describes output Y_{it} as a function of a vector of inputs X_{it} and an error term made up of three components: α_i representing farm-specific unobserved heterogeneity or fixed effects, $v_{it} \sim N(0, \sigma_v^2)$ representing the standard error term, and, finally, the non-negative, error term u_{it} following a half normal distribution[13], reflecting the shortfall of a farmer's output from the production frontier, due to technical inefficiency.

Equation (2) presents u_{it} as a function of farm-specific, time-varying inefficiency determinants (Z_{it}) with error term $\varepsilon \sim N^{+}(\mu, \sigma_u^2)$ which is independent of Z_{it}. The data set analyzed does not contain information on farm-specific time-varying multi-factor inefficiency determinants. We account for these variables by a general time trend (*TREND*).

Stochastic frontier analysis using panel data began with Pitt and Lee (1981) and Schmidt and Sickles (1984) who used conventional panel data methods to account for unobserved individual heterogeneity. In general, these methods are limited and inappropriate because they treat inefficiency as time-invariant. Moreover, both time-effects and individual-specific effects are not controlled for, thus confounding inefficiency. Battese and Coelli (1992, 1995) allowed inefficiency to vary across time, but individual effects were not controlled for (Greene 2005).

Greene (2005) introduced a "true fixed effects model" which includes a set of individual dummies to capture fixed effects. The disadvantage of this model is the

[13] Other possible distributions for u_{it} are the exponential distribution (Meeusen and van den Broeck (1977), the truncated normal distribution (Stevenson, 1980) and the gamma distribution (Greene, 1980). Ritter and Simar (1997) recommend the half normal, if the sample size is 'large', i.e. several hundreds of observations, because in that case it produces more precise estimates than its alternatives. Moreover, it is simpler than the truncated normal or gamma.

incidental parameters problem[14] when the number of firms is large which may lead to a biased and inconsistent estimator of efficiency scores. Greene (2005) also introduced the random effects stochastic frontier model. However, this model is based on the assumption that the unobserved factors are uncorrelated with the explanatory variables which is likely to be violated in case studies like the present. Wang and Ho (2010) show that model transformation, i.e. first-differencing or with-in transform, can be performed to eliminate fixed individual effects in (1). They furthermore show that there is also no incidental problem in this model and that Maximum Likelihood (ML) is consistent. This paper applies this method.

A translog stochastic frontier production function is usually chosen for (1), since it has fewer estimation restrictions than alternatives like the Cobb-Douglas production function[15] (Christensen et al. 1973). For the *i*th farmer at time *t*, the translog stochastic frontier production function with, say, 4 inputs, reads[16]:

$$lnY_{it} = \beta_0 + \beta_w lnW_{it} + \sum_{j=1}^{3} \beta_j lnX_{ijt} + \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3} \beta_{jk} lnX_{ijt} lnX_{ikt} + \sum_{j=1}^{3} \beta_{wj}\, lnW_{it} lnX_{ijt} + \frac{1}{2}\beta_{ww}(lnW_{it})^2 + \alpha_i + v_{it} - u_{it} \qquad (3)$$

where β_{jk}=β_{kj}. Y_{it} is the total value of *Output*, W_{it} is irrigation water (measured in m^3), and X_{i1t}, X_{i2t} and X_{i3t} denote *Land* (measured in mu[17]), *Labor* (measured as number of workers employed) and *Other Inputs* (measured in RMB), respectively.

2.3.4 Measurement of IWTE[18]

We use production function (3) to calculate $IWTE_{it}$, which, as mentioned above, is the ratio of minimum feasible use to observed use of irrigation water, conditional on given production technology, levels of output and other inputs. Hence:

$$IWTE_{it} = min\{\lambda : F(X_{it}, \lambda W_{it}; \beta) \geq Y_{it}\} \rightarrow (0, 1) \qquad (4)$$

In (4) λ denotes $IWTE_{it}$, W_{it} represents the actual amount of irrigation water used and λW_{it} is the "best practice" (i.e. minimum feasible) quantity of irrigation water. Y_{it} is the actual output, X_{it} and β as defined in (1).

[14] The 'incidental parameters problem' refers to the fact that the maximum likelihood estimator of the fixed effects model is inconsistent, if *N* is very large, because the number of nuisance parameters increases with sample size (Neyman and Scott, 1948).
[15] The Cobb-Douglas production function assumes $\beta_{ww} = \beta_{wj} = \beta_{jk} = 0$ in (3).
[16] For a full description of inputs used in this study, see section 4.
[17] 1 mu is 0.0667 ha.
[18] The method presented below has also been applied by e.g. Wu (2010) to measure environmental efficiency in China.

To obtain $IWTE_{it}$, we rewrite (1) and (3) as follows (Reinhard et al. 1999):

$$Y_{it} = F(X_{it}, W_{it}^F; \beta)\exp(v_{it}) \quad (5)$$

and

$$lnY_{it} = \beta_0 + \beta_w lnW_{it}^F + \sum_{j=1}^{3} \beta_j lnX_{ijt} + \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3} \beta_{jk} lnX_{ijt} lnX_{ikt}$$

$$+ \sum_{j=1}^{3} \beta_{wj}\, lnW_{it}^F lnX_{ijt} + \frac{1}{2}\beta_{ww}(lnW_{it}^F)^2 + \alpha_i + v_{it} \quad (6)$$

where W_{it}^F is the minimum feasible use of irrigation water (i.e. EE^* in Figure 2.3). Setting actual production equal to production under no technical inefficiency ($u_{it} = 0$) when using W_{it}^F while producing the same level of output (Y_{it}), implies setting equation (3) equal to equation (6). This gives:

$$\beta_w lnW_{it}^F + \sum_{j=1}^{3} \beta_{wj} lnW_{it}^F lnX_{ijt} + \frac{1}{2}\beta_{ww}\,(lnW_{it}^F)^2$$

$$= \beta_w lnW_{it} + + \sum_{j=1}^{3} \beta_{wj} lnW_{it} lnX_{ijt} + \frac{1}{2}\beta_{ww}(lnW_{it})^2 - u_{it} \quad (7)$$

$IWTE_{it}$ can now be expressed as:

$$IWTE_{it} = \frac{W_{it}^F}{W_{it}} \quad (8)$$

or $$lnIWTE_{it} = lnW_{it}^F - lnW_{it} \quad (9)$$

From (7) and (9), we get

$$\frac{1}{2}\beta_{ww}(lnIWTE_{it})^2 + \left(\beta_w + \sum_{j=1}^{3} \beta_{wj} lnX_{ijt} + \beta_{ww} lnW_{it}\right) ln(IWTE_{it}) + u_{it} = 0 \quad (10)$$

From (10), $IWTE_{it}$ for individual farmer *i* at time *t* can be obtained as:

$$IWTE_{it} = exp\left(\frac{-\xi_{it} \pm \sqrt{\xi_{it}^2 - 2\beta_{ww} u_{it}}}{\beta_{ww}}\right) \quad (11)$$

where $\xi_{it} = \beta_w + \sum_{j=1}^{3} \beta_{wj} lnX_{ijt} + \beta_{ww} lnW_{it}$ (12)

2.4 Sample design and data

The data used to estimate the above model is obtained from a survey conducted during the period 1999-2005 by Northwest A&F University, Shaanxi Province. The main goal of the survey was to elicit information on farmers' use of inputs and outputs in agricultural production. The stratified random sample was selected as follows. First, the sampling area was defined as the nine largest irrigation districts in the Guanzhong Plain comprising 80 per cent of the total irrigation area. Secondly, 80 irrigation canals out of a total of 5997 in the nine irrigation districts were selected, proportional to the number of canals in each irrigation district. Both reformed and un-reformed, and upstream and downstream canals were included. Next, 10 farmers were randomly chosen at each selected canal with 5 farmers in the upper and 5 in the downstream regions. Thus, a total number of 800 farmers were included in the sample. Since 177 farmers failed to provide all the requested information for all the six consecutive years of the survey, an unbalanced panel of 4,502 observations resulted. Drop out from the sample was random.

Every individual farmer was asked to record inputs and outputs for each year via a diary. The respondents were awarded a small allowance for providing the required information. The diaries were collected between May and June when the wheat harvest was completed.

Corn and wheat were the two main crops in the Guanzhong Plain, in addition to cash crops like kiwis, cotton and fruits. For each crop, the information collected related to *Output* (yield times crop price received) and the following inputs: (1) sown area (*Land*); (2) number of family labors (*Labor*); (3) *Other Inputs*, i.e. the sum of the values of fertilizers, machinery, pesticides, plastic sheeting, etc. and (4) *Water*. Regarding the input of water, the farmers were asked to report for the entire growing season for each crop the total number of irrigations, and per irrigation the date, duration, irrigation equipment applied, volume, and the amount paid (Wang et al. 2006a). An additional survey was held among canal managers in the research area between November and December each year. Interviewers asked canal managers questions on their personal characteristics, water price charged, irrigated areas via their canals, pattern of canal management and so on. Information collected via the canal managers survey was used as a check on water input information provided by the farmers. Generally, farmers were found to provide accurate information (Wang et al. 2006a).

Table 2.3 Descriptive statistics of the variables in the stochastic frontier model

Year	Variable	Farmer model				Canal model			
		Mean	S.E.	Min.	Max.	Mean	S.E.	Min.	Max.
2000	*Output* (yuan)	5679	5049	724	52000	53609	2914	21414	162635
	Land (mu)	13.12	5.73	2.8	72	123.0	32.66	47.1	191
	Labor (number)	2.6	0.96	1	7	24.3	4.68	10	35
	Other Inputs (yuan)	1657	921	153	6700	15960	5504	7161	31369
	Water (m^3)	2218	1528	120	11677	20783	1065	5228	54149
2001	*Output* (yuan)	5669	3871	261	46764	55542	2422	20374	142746
	Land (mu)	13.07	5.41	2.6	42	126.7	32.55	57.1	202.1
	Labor (number)	2.67	1.05	1	8	25.9	5.30	13	41
	Other Inputs (yuan)	1766	1379	36	18698	16882	8438	6166	49862
	Water (m^3)	2468	1786	49	13333	23934	1248	1537	61833
2002	*Output* (yuan)	5885	3848	140	35292	57608	2665	20104	172815
	Land (mu)	12.76	5.07	1.6	31.4	124.6	32.45	49.6	215.05
	Labor (number)	2.84	1.1	0.5	6	27.8	6.68	14	51
	Other Inputs (yuan)	1921	1245	155	10027	18689	8351	5247	49332
	Water (m^3)	2305	1580	94	13025	23934	1248	1537	61833
2003	*Output* (yuan)	6171	4070	362	46042	60246	2613	18229	155059
	Land (mu)	12.5	5.4	1.8	46	120.8	34.24	39.98	229.5
	Labor (number)	2.52	0.88	1	7	24.32	3.97	11	35
	Other Inputs (yuan)	1870	1303	160	12324	17940	8478	4994	48457
	Water (m^3)	1745	1227	30	10895	16856	8709	2871	47759
2004	*Output* (yuan)	6943	3722	1010	29302	66176	2387	10305	138919
	Land (mu)	12.37	5.1	2.4	41.5	117.9	35.09	23.5	216.8
	Labor (number)	2.56	0.93	1	6	24.41	5.05	4	37
	Other Inputs (yuan)	1793	1096	115	8695	17209	7361	2354	46406
	Water (m^3)	2109	1456	44	14238	20099	1067	507	64957
2005	*Output* (yuan)	6718	4314	738	48531	63793	2722	7683	146168
	Land (mu)	12.33	5.05	2	40	117.98	35.57	22.79	235.67
	Labor (number)	2.49	0.89	1	6	23.85	4.50	5	36
	Other Inputs (yuan)	2060	1219	250	8608	19586	8233	2616	44747
	Water (m^3)	2193	1627	75	13427	20982	1316	1335	69209

Source: The survey.

We lumped the values of outputs and inputs for all the crops in a year together for three reasons. First, most farmers in the study area grow the same crop during the same season. Secondly, we analyze farm-specific *IWTE* which allows the use of aggregated data and the same production technology model for all farmers. For other studies relating to China that use aggregated data, see e.g. Yao and Liu (1998) and Zhang et al., (2011). Finally, Wang et al. (2010) found small differences in water use for the two main crops, wheat and corn, for a region similar to the Guanzhong Plain. The revenues and input costs were deflated by the price index for Shaanxi. Canal data were obtained by aggregating the data for the farmers belonging to the same canal. Descriptive statistics of inputs and output (both farm and canal level) are presented in Table 2.3.

2.5 Empirical results

2.5.1 The translog production function

The stochastic farmer and canal production functions (1) and the multi-factor inefficiency models (2) are estimated using the Maximum Likelihood (ML) procedure in the Stata software package (version 11, StataCorp, College Station, TX; see Wang and Ho (2010) for details about the ML procedure). As a first step, we tested the functional form, i.e. Cobb-Douglas (H_0) versus translog (H_1) production function. The former is nested within the latter. On the basis of the log likelihood test statistic, we rejected the Cobb-Douglas for both the farmer (χ^2_{10}=86.96) and the canal model (χ^2_{10}=34.70)[19]. Additional support for the translog production function is provided by the significance of various of the cross products and squared terms in both models.

The estimates are presented in Table 2.4. The following results emerge. First, the null hypothesis that farmers are technically efficient (u_{it} in (1) equals 0), is rejected at 1% significance level. The estimated σ_u^2s are highly significant and equal to 0.3371 and 0.2614 in the farmer and canal model, respectively. The percentage of variance explained by technical inefficiency, $\sigma_u^2/(\sigma_u^2 + \sigma_v^2)$ is 82.10 per cent for the farmer model and 92.65 per cent for the canal model, respectively, indicating that farm (canal)-specific technical inefficiency is an important contributor in explaining *total variability* of output produced. In the inefficiency equation, the coefficients of *Trend* (-0.2618 in the farmer model) and (-0.2259 in the canal model) are negative and significant, indicating that inefficiency decreases with time. Thirdly, due to aggregation, several of the coefficients and standard errors in the canals model deviate from those in the farmer model.

[19] The likelihood-ratio test statistic $\lambda = -2\{[\text{logLikelihood}(H_0)] - [\text{logLikelihood}(H_1)]\}$ follows a χ^2distribution (Battese and Coelli 1995). The null hypothesis is $\beta_{ww} = \beta_{Wj} = \beta_{jk} = 0$ with 10 degrees of freedom. The critical value for the 1% significance level is 23.21.

Table 2.4 The estimated stochastic farmer and canal production frontier models

Dependent variable:	Farmer model			Canal model		
Ln(*Output*)	Coefficient	S.E.	p-value	Coefficient	S.E.	p-value
Independent variables						
Ln*Land*	0.3555	0.2238	0.112	-0.1415	1.3161	0.914
Ln*Labor*	0.1972	0.2219	0.374	-1.3768	1.0912	0.207
Ln(*Other Inputs*)	0.8401***	0.1822	0.000	3.0499***	1.0662	0.004
Ln*Water*	0.5808***	0.1224	0.000	0.8932	0.5711	0.118
Ln*Land**Ln*Labor*	-0.0486	0.0523	0.353	0.0054	0.2432	0.982
Ln*Land**Ln(*Other Inputs*)	-0.1797***	0.0346	0.000	-0.5618***	0.1722	0.001
Ln*Land**Ln*Water*	0.1198***	0.0270	0.000	0.2691**	0.1179	0.023
Ln*Labor** Ln(*Other Inputs*)	0.0320	0.0329	0.331	0.1584	0.1505	0.292
Ln*Labor**Ln*Water*	-0.0404	0.0251	0.107	0.0582	0.1050	0.580
Ln(*Other Inputs*)*Ln*Water*	-0.0882***	0.0171	0.000	-0.0888	0.0694	0.201
Ln*Land**Ln*Land*	0.2158***	0.0666	0.001	0.7238**	0.3587	0.044
Ln*Labor**Ln*Labor*	-0.0231	0.0748	0.758	-0.2537	0.3196	0.427
Ln(*Other Inputs*)*Ln(*Other Inputs*)	0.0896***	0.0312	0.004	0.0403	0.1506	0.789
Ln*Water**Ln*Water*	-0.0203	0.0166	0.223	-0.1428**	0.0652	0.028
Multi-factor Inefficiency model						
TREND	-0.2618***	0.0542	0.000	-0.2259**	0.0956	0.018
σ_u^2	0.3371***	0.0467	0.000	0.2614***	0.0951	0.000
σ_v^2	0.0735***	0.0018	0.000	0.0207***	0.0016	0.000
Log likelihood	-542.0270			179.8808		
Wald test	2512.38***		0.000	499.72***		0.000
Observations	4502			469		

Note: Standard errors in parenthesis.
$^{*}p<.10$, $^{**}p<.05$, $^{***}p<.01$.

The output elasticities with respect to each input are calculated for each model and shown in Table 2.5. The elasticity of a variable with an interaction term was calculated at the average of the interacting term. In the farmer model, output elasticity of *Other Inputs* is highest at 0.4294, followed by 0.4124 for *Land*. The output elasticity of *Labor* is negative and insignificant. A possible explanation is that labor is measured as the number of workers in the family rather than as hours worked. The elasticities of *Other Inputs* and *Labor* in the canal model are close to those in the farmer model whereas those for *Land* and *Water* are higher. Note that the elasticity for *Water* is low in both models. A 1 per cent increase in irrigation water leads to a 0.04 per cent increase of output in the farmer model and a 0.10 per cent increase in the canals model. These results indicate that for the period under investigation water scarcity is not yet seriously limiting output. The sum of the elasticities with respect to the four inputs (0.8733 in the farmer model and 0.9557 in the canal model, respectively) indicates decreasing returns to scale for both models.

Table 2.5 Elasticity per input

Elasticity	*Land*	*Labor*	*Other Inputs*	*Water*	Returns to scale
Farmer model	0.4124	-0.0084	0.4294	0.0398	0.8733
Canal model	0.5069	-0.0569	0.4041	0.1015	0.9557

2.5.2 Efficiency scores

Tables 2.6 and 2.7 present estimated yearly average Irrigation Water Technical Efficiency (*IWTE)* scores for farmers and canals, respectively, in the form of frequency distributions by deciles. For farmers the overall average over the 6-year period is 0.1577, which is substantially below that of canals (0.4877), due to aggregation. Table 2.6 shows extremely low efficiency for farmers in 2000. The average is 0.0795 indicating that *ceteris paribus*, the farmers' average net income can be maintained while using 92.05 per cent less irrigation water. This situation has, however, substantially improved during the research period. From the year 2000 onwards, the average increased from 0.1063 in 2001 to 0.2316 in 2005. In 2005, under the current irrigation technologies, almost 77 per cent of irrigation water can be saved while keeping current level of output and other inputs than water constant. Table 2.7 shows a similar trend for canals.

Table 2.6 Frequency distribution of estimated farmer *IWTE*

Year	<0.1	0.1–0.2	0.2–0.3	0.3–0.4	0.4–0.5	>0.5	Average
2000	69.38%	20.90%	6.15%	1.83%	0.66%	0.40%	0.0795
2001	56.88%	28.49%	12.29%	2.88%	0.93%	0.40%	0.1063
2002	60.11%	27.14%	14.21%	4.19%	1.46%	0.66%	0.1128
2003	38.34%	19.00%	20.74%	16.12%	7.44%	1.98%	0.1889
2004	33.15%	15.06%	16.52%	20.84%	12.08%	4.37%	0.2226
2005	35.53%	15.33%	13.70%	16.64%	12.22%	9.26%	0.2316

Table 2.7 Frequency distribution of estimated canal *IWTE*

Year	<0.1	0.1–0.2	0.2–0.3	0.3–0.4	0.4–0.5	>0.5	Average
2000	2.63%	15.79%	18.42%	18.42%	14.47%	30.26%	0.3749
2001	5.26%	10.53%	9.21%	14.47%	23.68%	36.84%	0.4176
2002	0.00%	8.75%	12.50%	15.00%	20.00%	43.75%	0.4495
2003	0.00%	5.06%	5.06%	11.39%	10.13%	68.35%	0.5464
2004	0.00%	2.53%	6.33%	10.13%	16.46%	64.56%	0.5540
2005	0.00%	2.53%	10.13%	11.39%	7.59%	68.35%	0.5770

2.5.3 Determinants of irrigation water technical efficiency

To get insight into the sources of variation in irrigation water use efficiency, especially the role of the management systems, we perform a second stage analysis of single-factor technical efficiency obtained by means of the stochastic frontier analysis (see above). Note that Battese and Coelli (1995) argues that a separate second-stage analysis is inconsistent because it is based on the assumption that technical efficiency scores are independently, identically distributed. In the author's view this assumption is violated because the scores are correlated with a set of uncontrolled variables. To obtain a consistent estimator, Battese and Coelli (1992, 1995) propose simultaneous estimation of the production function and the technical efficiency model. Reinhard et al. (2002), however, shows that separate second stage analysis is not inconsistent because the dependent variable is single-factor technical efficiency, which is calculated from the first-stage parameter estimates, unlike multi-factor technical efficiency which is estimated from the error component. Below we follow Reinhard et al. (2002) and apply a separate analysis. As a first step, we discuss the explanatory variables of the efficiency model[20].

2.5.3.1 Water availability

Wang et al. (2006b) shows that farmers' awareness of water scarcity decreases their use of irrigation water. Hence, in the case of ample water availability, there is less need to save water. Since water is not yet experienced as scarce in the study, we expect a negligible impact of water availability on farmers' water use efficiency.

2.5.3.2 Water price

The second explanatory variable is water price, which is made up of three components: resource fee, administration fee and institutional fee. The Provincial Price Bureau sets the resource fee, which varies across irrigation districts and canals according to water availability and demand, and the state of irrigation infrastructure. The Irrigation Administration Bureau in each irrigation district, which controls the main canals and allocates water to the sub-canals, decides on the administration fee. This component of the fee is intended to cover operations and management. The third component, the institutional fee, is set by the management of the sub-canals, though it should be below a ceiling fixed by the Irrigation Management Bureau. The total fee is collected from the farmers by the sub-canal manager and transferred to the Irrigation Management Bureau. For all types of management (reformed and unreformed), the first and most important component is volumetrically based. As noted above, in the Guanzhong Plain, as elsewhere in rural China, precise estimation of irrigation water use is complicated, because of absence of measuring stations. However, the information obtained via the survey is quite accurate. From the above it follows that *Water Price* acts as an allocation

[20] Some omitted variables, e.g. farmers' education level, are captured by the error term and eliminated by means of the fixed effects estimator that we have applied.

tool. It reflects opportunity cost of irrigation water, provides farmers with information on water availability, and induces them to save water. We, therefore, hypothesize that a higher price leads to higher water use efficiency.

2.5.3.3 *Disclosure*

The irrigation management is required by the Irrigation Management Bureau to regularly publish information on its decisions and operations. The information disclosed includes irrigated area, water fee paid and volume of water used per farmer. In addition, each of the three components of the water price (resource fee, administration fee and institutional fee) is published. One reason for *Disclosure* is reduction of corruption. Under the collective management system, village leaders tended to charge a markup on the administration and institutional fees. *Disclosure* is intended to reduce this practice. Furthermore, Wang et al. (2006b) argues that transparency (i.e. managers share information with farmers) leads to mutual accountability and trust. Another positive impact of *Disclosure* is that information on the price, its components and water use by peers stimulates farmers to economize on water use (Wang et al. 2010). Particularly, water use by one farmer may serve as a benchmark and incentive to improve water use efficiency of other farmers. Hence, we expect *Disclosure* to positively impact on farmers' water use efficiency.

2.5.3.4 *Management form*

As outlined above, compared to the base case of *Unreformed*, we expect the three types of reforms to have a positive impact on water use efficiency. The expected signs of the control variables and descriptive statistics are given in summarized in Table 2.8.

Table 2.8 Definitions, expected impacts, and descriptive statistics of the covariates of the linear efficiency model

Variable	Definition	Expected sign	Mean	S.D.	Min.	Max.
Water Availability	Water flow per canal per year (10,000 m^3)	-/+	31.91	28.44	0.44	186.24
Disclosure	Dummy variable; 1 if information is disclosed, 0 otherwise	+	0.84	0.37	0	1
Water price	Water price per canal (yuan/m^3)	+	0.22	0.06	0.07	0.42
COM	Dummy variable; 1 if the canal is managed under *COM*, 0 otherwise	+	0.63	0.48	0	1
JSC	Dummy variable; 1 if the canal is managed under *JSC*, 0 otherwise	+	0.16	0.37	0	1
WUA	Dummy variable; 1 if the canal is managed under *WUA*, 0 otherwise	+	0.05	0.22	0	1

Source: The survey.

2.5.4 Fixed effects Tobit model

Since the dependent variable is restricted to the interval [0, 1], we estimate the farmer and canal efficiency models as a fixed effects, [0, 1] bounded, Tobit model. Lancaster (2000) argues that nonlinear fixed effects models suffer from the incidental parameter problem. However, on the basis of Monte Carlo simulations Greene (2004) shows that the ML estimator of the fixed effects Tobit is not biased. The estimator has been applied in a substantial literature including Ali et al. (2011) and Odeck and Bråthen (2012). Below we follow Greene (2004). The second-stage fixed effects Tobit model, based on the conceptual model presented in section 2.3, reads[21]:

$$IWTE_{it}^{*} = \gamma_0 + \gamma_1 \log(Water\ Availability_{it}) + \gamma_2 \log(Water\ Price_{it})$$
$$+\gamma_3 Disclosure_{it} + \gamma_4 CON_{it} + \gamma_5 WUA_{it} + \gamma_6 JSC_{it} + \omega_i + \varepsilon_{it}$$
$$IWTE_{it} = \begin{cases} 0 & if\ IWTE_{it}^{*} < 0 \\ IWTE_{it}^{*} & if\ 0 \le IWTE_{it}^{*} \le 1 \\ 1 & if\ IWTE_{it}^{*} > 1 \end{cases} \tag{13}$$

where $IWTE_{it}^{*}$ is a latent variable referring to $IWTE_{it}$, $\gamma_0, \gamma_1, \dots, \gamma_6$ are unknown parameters to be estimated, ω_i represents fixed effects, and ε_{it} is an *iid* error term.

Table 2.9 presents the estimates. We first discuss the farmer model. The main conclusions are the following. First, the estimated model is in line with expectations, as discussed above and summarized in Table 2.8. Log(*Water Availability*) has a significant positive impact on farmer water use efficiency, although the coefficient is extremely small and of little economic or practical significance. Particularly, ceteris paribus, an increase of water flow by 10 per cent increases farmer technical efficiency on average by 0.06 percentage point only. Log(*Water Price)* also has a positive, significant, but larger effect on efficiency. An increase of, say, 10 per cent leads to an increase of efficiency by 0.4 percentage points. The impact of *Disclosure* is also positive and highly significant. *Disclosure* provides farmers with information on irrigation details of other farmers, which serves as an incentive to improve water use efficiency. It also contributes to price awareness, which further stimulates efficiency. The partial effect means that efficiency increases by 7 percentage points when *Disclosure* is introduced.

[21] *Water price* was deflated by the price index for Shaanxi.

Table 2.9 The farmer and canal fixed effects Tobit efficiency models

Dependent variable: *IWTE*	Farmer model			Canal model		
	Coefficient	S.E.	p-value	Coefficient	S.E.	p-value
Log(*Water Availability*)	0.0064**	0.0028	0.022	-0.0123	0.0083	0.139
Disclosure	0.0703***	0.0051	0.000	0.0991***	0.0139	0.000
Log(*Water Price*)	0.0415***	0.0101	0.000	0.1946***	0.0336	0.000
COM	0.0578***	0.0083	0.000	0.0372	0.0241	0.123
JSC	0.0866***	0.0115	0.000	0.1004***	0.0332	0.003
WUA	0.1303***	0.0145	0.000	0.1226***	0.0418	0.003
Log likelihood	4023.88			450.15		
Number of observations	4502			469		

Note: Standard errors in parenthesis.
*p<.10, **p<.05, ***p<.01.

The coefficients of *COM*, *WUA* and *JSC* (relative to *Unreformed* as base case) are all positive and highly significant, suggesting that the reforms have substantially improved farmers' water use efficiency. This is due to the fact that the reform, irrespective of the reform pattern, has transferred the canal management responsibilities to organizations that have incentives to improve the performance of the irrigation system, and of water use efficiency. *JSC* and especially *WUA* with partial effects of 8.6 and 13.1 percentage points, respectively, are more successful in improving efficiency than *COM* (with a partial effect of 5 percentage points). A possible explanation is that under *WUA* and *JSC* farmers are better informed about, and more involved in, water saving than under *COM*. As argued by Wang et al. (2006) farmer participation is essential to the success of irrigation management reforms. World Bank (2003) has reported similar outcomes.

The canal model is less clear-cut than the farmer model, which is related to the smaller number of observations. Particularly, *Log(Water Availability)* and *COM* are insignificant at conventional levels. The coefficients of *Disclosure*, *Log(Water Price)* and *JSC* are larger than in the farmer model while the other are smaller. Moreover, all the standard errors are larger, as expected. Similar differences between micro and aggregate estimation results have been obtained in a wide range of other fields, such as labor economics (Heyman et al. 2007) and consumption growth (Attanasio and Weber 1993). The main reason is that (spatial) aggregation ignores heterogeneity among individuals and thus causes measurement biases (Blundell and Stoker 2005). Therefore, micro level analysis is usually preferred to macro/aggregate level analysis in explaining individual behavior.

2.6 Conclusions and policy implications

This paper analyzes irrigation water technical efficiency and its determinants at farmer and canal level in nine irrigation districts in the Guanzhong Plain on the basis of an unbalanced panel data set of 800 farmers observed during the period 2000-2005. The efficiency measure used is single-factor technical efficiency, which is defined as the ratio of the minimum feasible water use to observed water use, given output and the quantities of other inputs. A translog production function was estimated by panel data stochastic frontier maximum likelihood, which eliminated fixed individual effects through within-transform. In the second step, we estimated a fixed effects, bounded Tobit panel data model of the impacts of water availability, water price and disclosure on irrigation water efficiency.

The main results are the following. First, the output at both farm and canal level was adequately modeled by the translog production function in terms of the inputs, land, labor, water, and other inputs. The estimated translog production function was used to estimate single factor technical efficiency of irrigation water (*IWTE*). Although *IWTE* improved during the observation period, there is still a large potential for saving irrigation water. Since China is going to experience substantial water shortage problems in the near future with wide ranging domestic and international ramifications, further improvement of *IWTE* is an extremely important policy objective.

The second-step analysis revealed that for both farmers and canals, water price has a significant positive impact on irrigation water use efficiency. Hence, it is a potential policy handle. However, its impact at present is still very moderate. In order to "bite", substantial price hikes are needed. Yet, it is generally acknowledged that the price charged for irrigation water in China is far below its value (Yang et al. 2003; Lohmar et al. 2007). The main reason is that increasing rural income is a primary policy goal of the Chinese government, since the income gap between rural and urban has been widening substantially over the past decades. There is a widespread belief among Chinese policymakers, but also elsewhere in the Chinese society, that a higher price for irrigation water is at odds with the objective of narrowing the income gap (Johansson et al. 2002; Tsur et al. 2004). There is support for this belief. For example, in our sample, the cost of irrigation water accounts for 11 per cent of crop profit and 5 per cent of farm household income, although there is a tendency for these percentages to decrease. However, water price should reflect its marginal social revenue. Higher price improves water use efficiency which contributes towards agriculture sustainability in the long run. Again, the income loss due to increasing water price can be partly offset by water conservation by adopting water saving technologies or by switching to lucrative cash crops. See also Wang et al. (2010) who found that raising water price does not necessarily adversely affect household income. Moreover, to mitigate negative income effects, the price increases should be gradual and accompanied by disclosure on the rationale, and by promotion of water saving techniques. A possible drawback of higher price, as pointed out by Liao et al. (2008), is that some farmers may react by giving up farming. The drop out of the farmers is no problem in a sense that the plots are small and that there is too much labor in agriculture. It is the interest of society that land is reorganized to the farmers who are more water efficient. Meanwhile, action should be taken to prevent that higher water prices induce farmers to switch to groundwater. However, the risk of such a switch is rather small because the pumping costs of groundwater have been increasing due to the fall of the water table. Another deterrent is that groundwater has the potential risk of soil salinization.

We have also found that disclosure of management procedures, water use and water price plays an important positive role in water use efficiency. So, effort should be made to actually implement disclosure everywhere, amongst others via promotion by the Irrigation Management Bureaus. Another, and probably the most important, outcome is that management reform in general, particularly the introduction of *JSCs* and especially of *WUAs,* has a substantial impact on efficiency. Since the proportion of *WUAs* and *JSCs* is still small, these management types should be strongly promoted by amongst others the provincial and local. The efforts should not be restricted to management reform, but also include related issues such as the promotion of adoption of water-saving technologies.

The results obtained in this paper for the Guanzhong Plain are relevant to other arid and semi-arid agricultural areas in China. As mentioned in the Introduction, 75 per cent of China's grain production comes from irrigated land, which accounts for 50 per cent of China's total arable land. Therefore, efficient irrigation water use is of crucial importance for China's sustainable food production. The results discussed above show that management plays a crucial role in irrigation water use efficiency. Hence, it is important to promote cooperative irrigation water use management in other important agricultural production as well.

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Chapter 3

Estimation of awareness and perception of water scarcity among farmers in the Guanzhong Plain, China, by means of a structural equation model[22]

Abstract: This paper applies a structural equation model (SEM) to analyze the formation of awareness and perception of water scarcity, based on a cross-sectional dataset of 446 farmers in the Guanzhong Plain, Shaanxi Province, China. We find that age, percentage of time spent on farming and social network are the main determinants of awareness. Water price and drought experience are the most important explanatory variables of perception. In addition, awareness and perception strongly interact. The results obtained in this paper are relevant for policymaking, since environmental behavior, which includes efficient use of natural resources, tends to improve if supported by internalization of social norms, which in its turn, is promoted by awareness and perception. From the analysis it follows that spreading information via social networks, rather than via the media, is an important vehicle to enhance awareness and perception and thus to improve irrigation water use efficiency. Special attention should be paid to part-time farmers who are limited in directly perceiving water scarcity. Finally, more use should be made of the price mechanism to strengthen perception and awareness.

Keywords: Awareness, Perception, Structural equation modeling, Water scarcity, China

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3.1 Introduction

Water scarcity in Northern China is an important resource problem with far reaching environmental impacts and threats to food security and socio-economic development in all China (Jiang, 2009). Optimal use of the limited water resources is not only important to farmers but to virtually all economic sectors, to households and to policy makers. Since agriculture consumes approximately 70% of the total water resources in Northern China and has low water use efficiency (Tang et al., 2012), insight is needed into farmers' irrigation water use as a step towards conservation.

We hypothesize that farmers' water use strongly relates to their awareness and perception of water shortage. Although to the best of our knowledge, this hypothesis has not been investigated yet, there is indirect evidence for it. For instance, based on a sample of 1,200 respondents, Gregory and Di Leo (2003) found that households with lower water usage display greater awareness of water conservation issues. Similar empirical evidence was obtained by Jorgensen et al. (2009) and Dolnicar et al. (2012).

Standard economic models assume that producers conclude economic decisions based on profit maximization. One disadvantage of these models is that they neglect psychological and sociological factors, which also affect economic behavior. Specifically, Folmer (2009) argues that human behavior, including economic behavior, is strongly influenced by awareness, perceptions, expectations and habits. Weck-Hannemann and Frey (1995) argue that intrinsic motivation and internal sanctions promote environmentally-friendly behavior. Intrinsic motivation and internal sanctions in their turn strongly depend on environmental awareness and perception, which thus determine attitudes that affect future behaviors (Ramsey and Rickson, 1976; Napier and Napier, 1991; Bayard and Jolly, 2007). Hence, to comprehend and influence farmers' responses to water scarcity, insight into their awareness and perception of the problem is a prerequisite for the development of adequate and effective policy handles.

Despite the fact that the Chinese government has been actively promoting water-saving via extension programs and low-interest loans, the adoption of water-saving technologies is still limited in Northern China (Liu et al., 2008). Blanke et al. (2007) states that the reason of the low adoption rate is lack of appropriate incentives. Ervin and Ervin (1982) argue that in the decision-making process of technology adoption, awareness of the problem that the technology is supposed to solve plays a crucial role.

Particularly, only when water scarcity is perceived as a problem, incentives can be successfully implemented to stimulate adoption of water-saving technologies.

Despite its importance for scientific research and for policymaking, awareness and perception of water scarcity are poorly understood and have received little attention in literature. One of the few exceptions is Wang et al. (2009), who found that in northwestern China, 30% of the farmers and community leaders were not aware of water scarcity in their regions. Wang et al. (2006) studied the relationship between awareness and perception of water scarcity on the one hand and water saving on the other. He found that in communities where leaders are aware of water scarcity in their villages, water use per hectare was lower than in villages where awareness was lacking. These studies do not, however, address the formation of awareness and perception of water scarcity. Further research is thus needed so that policy makers can more accurately develop policy handles for water conservation in agriculture. This paper tries to fill this gap.

The objective of this paper is to examine the socio-demographic, economic and psycho-sociological determinants of farmers' awareness and perception of irrigation water scarcity in the Guanzhong Plain, Shaanxi Province, China. The structure of the paper is as follows. Section 3.2 presents the conceptual model. Methodology and data are described in Section 3.3. Section 3.4 discusses the empirical results and Section 3.5 concludes.

3.2 Conceptual model

Below, we develop the conceptual model of awareness and perception of irrigation water scarcity (i.e. the main variables and their relationships). We first discuss the endogenous variables awareness and perception, and next the exogenous variables.

3.2.1 Endogenous variables: awareness and perception

Despite the vast amount of research on awareness and the related notion of perception, the two different terms are still used interchangeably. Below, we first define each concept and next discuss their interaction.

3.2.1.1 Awareness of water scarcity

Sudarmadi et al. (2001) defines environmental awareness as the attention and concern (mindful and heedful) of individuals to environment problems. In other words, an aware individual is conscious of the threat of the problem, understands that he (she) may suffer from its consequences and, as a result, is concerned about it. When an environmental problem has been perceived (see below for a definition), awareness will further the comprehension, interpretation and evaluation of the perception such that a conclusion regarding the importance of the problem (ranging from not important to very important) can be drawn. In the present paper, a farmer is considered to be aware of water scarcity if it has his or her attention because it may affect output.

3.2.1.2 Perception of water scarcity

Sudarmadi et al. (2001) defines perception of an environmental problem as the recognition of it as a problem, based on memory and prior experience. People receive signals and stimuli from the social and physical environment around them and use them to build up an understanding of that environment. The stimuli and signals are subjectively evaluated to form perceptions through a cognitive process of interacting with that environment. Experience plays a crucial role in the process in forming perceptions (Diggs, 1991). There is a subjectively defined threshold below which the signal or stimulus does not lead to perception (Kates, 1971; Burton et al., 1993). Experience is thus effected by magnitude, frequency and timing of occurrence of the problem. There will be perception only when frequency and intensity exceed an individual-specific threshold. Hence, the status of water availability serves as an environmental stimulus, which must be intensive and frequent enough to trigger perception of water scarcity. Based on this definition, we assume that a farmer perceives water scarcity if he(she) reports of facing water scarcity problems in irrigating farmland (definition of the water scarcity problem) and understands that the problem may happen in the future (expectation).

From the above it follows that perception of water scarcity is the recognition of the state of water availability as problematic, whereas awareness refers to the attention to the state because of its impacts on output. Perception and awareness interact. First of all, perception is a basic determinant of awareness in that it triggers attention and concern (Endsley, 1995). By definition, awareness is the synthesis of the information triggered and transmitted by perception. Hence, when a farmer observes irrigation water scarcity, he may grow aware (heedful) because of possible yield losses. Note that perception only leads to awareness when it exceeds frequency and intensity thresholds (Merikle et al., 2001). For the present case study, farmers may not grow aware of water scarcity if they do not perceive water scarcity as a problem. Thus, we hypothesize that the more a farmer perceives water as scarce, the more aware he grows. There is also a reverse effect:

perception of water scarcity is influenced by awareness of it because awareness helps to recall past experiences and lowers the threshold of perceiving the stimulus. Awareness thus generates a higher probability of perceiving water scarcity.

3.2.2 Exogenous variables

Control variables of awareness and perception of irrigation water scarcity include socio-demographic factors, farming characteristics and access to information (see, amongst others, Van Liere and Dunlap, 1980; Jones and Dunlap, 1992 for reviews). Based on a brief literature review, we discuss the rationale of the inclusion of seven of these explanatory variables into the conceptual model, as well as their expected impacts.

3.2.2.1 Age

Since older farmers tend to have experienced more droughts and recall more than younger farmers, age is expected to positively impact awareness. However, younger farmers may be more concerned than older farmers because of a longer expected remaining lifespan, and thus, larger expected remaining lifetime earnings. Evidence supporting the former impact is provided by Lee and Zhang (2008) while the latter hypothesized effect is supported by Arcury and Christianson (1990), among others. Because of the opposing tendencies, the ultimate impact of age on awareness is an empirical matter. Regarding perception, we do not hypothesize a direct age impact, but rather, an indirect effect via perception.

3.2.2.2 Education

Education has been identified as an important determinant of environmental awareness. Stapp (1969) was the first to discuss the relationship. He showed that education makes individuals more knowledgeable and competent to interpret a complex phenomenon such as the environment. It enables them to acquire a proper understanding of the problem and thus contributes to their awareness. This hypothesis has been tested through a large body of studies (Jones and Dunlap, 1992; Dunlap et al., 2000; Feng and Reisner, 2011). For farmers in Gansu Province in northwestern China, Lee and Zhang (2008) found a strong relationship between education and awareness of desertification and Wei et al. (2009) between education and awareness of environmental degradation. Thus, a farmer’s level of education is assumed to positively impact on awareness of water scarcity. From its definition as the ability to recognize water scarcity as a problem based on memory and prior experience, we do not hypothesize a direct impact from education on perception but rather an indirect effect via awareness.

3.2.2.3 Drought experience

Burton and Kates (1964) are among the pioneers in finding that personal experience makes hazards more meaningful and leads to increased perception of them. Several studies support the hypothesis that drought experience is a key factor associated with heightened perception of it. For example, Woudenberg et al. (2008) found that among farmers in Frontier County, Nebraska, experience contributes to more accurate estimates of drought incidence. The reason is that the experience directly shapes an individual's memory and thus the recognition of, for example, a drought (Taylor et al., 1988). We hypothesize that the impact of drought experience on awareness is indirect via perception.

3.2.2.4 Price of irrigation water

Water price signals its scarcity, in the present case of irrigation water (Dinar and Saleth 2005). Note, however, that Huang et al. (2010) argues that the price of irrigation water is extremely low in China so that the farmers have little incentive to save water. Nevertheless, we hypothesize that the price of irrigation water serves as an important signal and thus positively impacts on the perception of irrigation water scarcity.

3.2.2.5 Social network

Social contagion theory (Burt, 1987) suggests that an individual's cognitive process by which he(she) collects and processes information to form perceptions, is influenced by her or his social network. Scherer and Cho (2003) argue that in risk perception analysis, the unit of analysis should not be an isolated individual, but rather the individual embedded in his or her social network. Hence, we expect perception of irrigation water scarcity to be positively influenced by a farmer's social network. Particular, the two elements of perception of scarcity, definition and expectation of water shortage, are influenced by one's social network. For instance, scarcity experiences of other farmers in the same region may "persuade" the farmer to perceive more clearly that irrigation water is scarce.

Brody et al. (2008) found that individuals are more likely to be aware of climate change, if her/his social network manifested high awareness of it. In the present study, we expect farmers' contacts with their neighbors, irrigation managers, water saving extension agencies and other farmers, to play an effective role in creating farmers' awareness of irrigation water scarcity.

3.2.2.6 Exposure to mass media

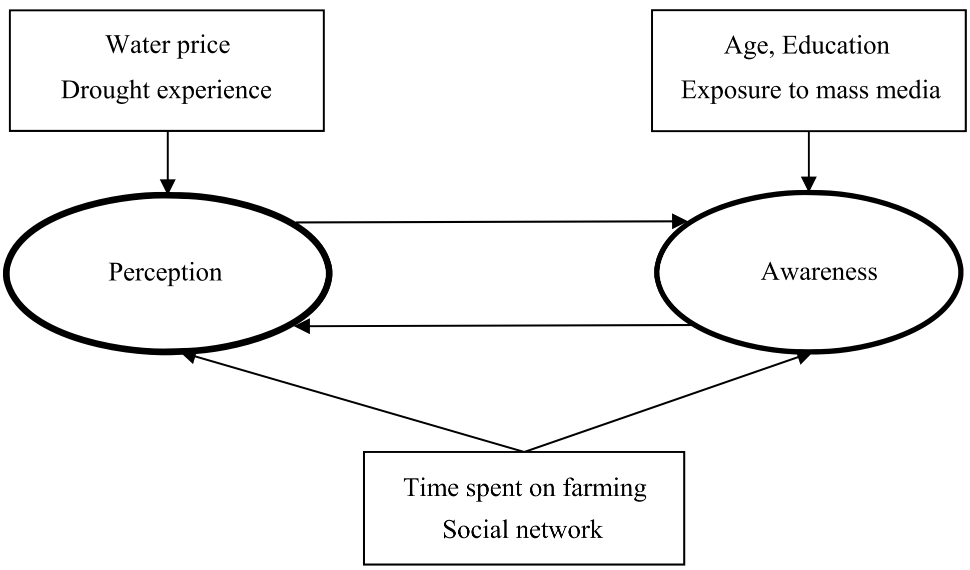
Reports on environmental issues create an imprint on people, inform them about the potential risks and thus establish awareness. There is a growing literature on the role of the media in influencing awareness (see amongst others, Korsching and Hoban, 1990; Lichtenberg and Zimmerman, 1999; Toma and Mathijs, 2007). Cheng (2009) observes that Chinese media tend to increasingly pay attention to environmental problems, such as desertification and drought. Hence, we hypothesize that farmers with more access to mass media are more aware of irrigation water scarcity.

3.2.2.7 Time spent on farming

Since the 1990s, due to mechanization, industrialization and free migration to urban areas, a growing number of farmers tend to spend less time on farming. We hypothesize that time spent on farming indicates the relative importance a farmer attaches to it. Hence, time spent on farming contributes to awareness of agricultural-related issues, such as water scarcity. Furthermore, the more time a farmer spends on his farm, the better (s)he will be informed about its state. Hence, we also hypothesize that farmers who spend more time on farming tend to have better chances to perceive water shortage on their farmlands.

The conceptual framework outlined above is summarized and presented in Figure 3.1.

Figure 3.1 The conceptual model



3.3 Methodology: Structural equation model with latent variables (SEM)

The model presented in Figure 3.1 is estimated as a Structural Equation Model with latent variables (SEM). Before presenting the model, we first briefly discuss the notion of a latent variable, which is a basic element of this kind of model (see amongst others Folmer, 1986 and the references therein, and Diamantopoulos et al., 2008).

3.3.1 Latent variables

A latent variable or theoretical construct refers to a phenomenon that is supposed to exist but cannot be directly observed. Examples are intelligence, socioeconomic status, welfare, awareness and perception. A latent variable is given empirical meaning (measured) by means of correspondence statements that relate it to a set of observed variables (indicators). For instance, intelligence is measured by intelligence tests and welfare by indicators like income, environmental quality, health care, safety and so on.

By the nature of their relationships to their indicators, latent variables can be classified into two categories, namely reflective and formative latent variables (Diamantopoulos et al., 2008). A latent variable is reflective, if causality flows from the latent variable to its indicators. The change in the indicators reflects the change of the latent constructs. In contrast, a latent variable is formative if causality is from the indicators to the latent construct. Distinction between the two categories is important because the nature of the latent construct determines the specification and the reliability of the measurement model. Misspecification of the measurement model leads to biased estimators and poor model fit (Diamantopoulos et al., 2008; Coltman et al., 2008).

In the conceptual model in Figure 3.1, there are four latent constructs: *Awareness*, *Perception*, *Network* and *Media*. We take *Awareness* and *Perception* as reflective because they are psychological constructs that determine the indicators such that a change of perception or awareness leads to changes of the measurement items such as farmers' responses to the measurement questions. *Network* and *Media*, however, are formative constructs because they are composed of the indicators in that a change in an indicator leads to a change in the corresponding construct.

3.3.2 SEM

Typical for a SEM is that it allows handling of latent and observed variables and their relationships within an integrated framework (Jöreskog and Sörbom, 2001). A SEM, as introduced by Jöreskog (1977), consists of two sub-models: a measurement model and a structural model. The measurement model specifies the relationship between the latent variables and their observed indicators while the structural model represents the relationships between the latent exogenous and latent endogenous variables as well as the relationships among the latent endogenous variables.

Equations (1) and (2) present the measurement models for the endogenous and exogenous variables, respectively.[23]

$$\mathrm{y} = \Lambda_y \eta + \varepsilon \tag{1}$$

$$\mathrm{x} = \Lambda_x \xi + \delta \tag{2}$$

where y is a $\mathrm{p} \times 1$ vector of endogenous observed variables, x a $\mathrm{q} \times 1$ vector of exogenous observed variables, η an $\mathrm{m} \times 1$ vector of latent endogenous variables, and ξ a $\mathrm{n} \times 1$ vector of latent exogenous variables. Λ_y and Λ_x are $\mathrm{p} \times \mathrm{m}$ and $\mathrm{q} \times \mathrm{n}$ matrices of coefficients (or loadings). Finally, ε and δ are $\mathrm{p} \times 1$ and $\mathrm{q} \times 1$ vectors of measurement errors of y and x, respectively.

The structural model reads as follows:

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta \tag{3}$$

where η and ξ are defined in (1) and (2), B is an $\mathrm{m} \times \mathrm{m}$ matrix with β_{ij} representing the effect of the jth endogenous latent variable on ith endogenous latent variable, Γ is an $\mathrm{m} \times \mathrm{n}$ matrix with γ_{ij} representing the effect of the jth exogenous latent variable on ith endogenous latent variable and ζ is a $\mathrm{m} \times \mathrm{m}$ vector of disturbances.

Model (1)-(3) is a general framework that encompasses a large number of sub-models ranging from first and second order factor analysis models, structural models for directly observed variables[24] and various types of regression models. The main advantages of applying a SEM are the following. First, it bridges the gap between theory (which is in terms of latent variables in the first place) and empirics (which is in terms of observed variables). Secondly, it reduces attenuation in the structural model because the explanatory variables in the measurement models have been purged of their measurement

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[23] It is possible to include intercepts in the measurement models and the structural model and to estimate the mean values of the latent variables (Jöreskog and Sörbom, 2001). However, the empirical analysis below is in terms of standardized variables and beta coefficients. Therefore, we delete the intercepts in model (1)-(3).
[24] Note that directly observed variables can be conveniently included in the structural model by specifying identity relationships between the latent and observed variables in the measurement model.

errors in the measurement models. Finally, SEM reduces the problem of multicollinearity (Folmer et al., 2010).

Estimation of model and testing (1)-(3) can be done by means of several software packages of which LISREL 8 (Jöreskog and Sörbom, 2001) and OpenMx (in R) are probably best known. The packages include several estimators (see Jöreskog and Sörbom (2001) for details). Most common is Maximum Likelihood (ML), which is genuine ML in the case of multinormally distributed observed variables. Furthermore, it is consistent and asymptotically normal in the case of non-normality, if the second order moments exist (Bollen, 1989). LISREL 8 and OpenMx also give hints about identification via a singularity check of the information matrix.

The conceptual model in Figure 3.1 in terms of the equations (1) - (3) reads:

$$\begin{bmatrix} Aware1 \\ Aware2 \\ Aware3 \\ Percep1 \\ Percep2 \\ Percep3 \\ percep4 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \lambda_{2,1} & 0 \\ \lambda_{3,1} & 0 \\ 0 & 1 \\ 0 & \lambda_{5,2} \\ 0 & \lambda_{6,2} \\ 0 & \lambda_{7,2} \end{bmatrix} \begin{bmatrix} Awareness \\ Perception \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \\ \varepsilon_7 \end{bmatrix} \tag{4}$$

$$\begin{bmatrix} Age \\ Edu \\ Waterprice \\ Experience \\ Media \\ Time \\ Network \end{bmatrix} = \begin{bmatrix} 1000000 \\ 0100000 \\ 0010000 \\ 0001000 \\ 0000100 \\ 0000010 \\ 0000001 \end{bmatrix} \begin{bmatrix} Age \\ Edu \\ Waterprice \\ Experience \\ Media \\ Time \\ Network \end{bmatrix} \tag{5}$$

$$\begin{aligned} \begin{bmatrix} Awareness \\ Perception \end{bmatrix} &= \begin{bmatrix} 0 & \beta_{1,2} \\ \beta_{2,1} & 0 \end{bmatrix} \begin{bmatrix} Awareness \\ Perception \end{bmatrix} \\ &+ \begin{bmatrix} \gamma_{1,1}\gamma_{1,2} & 0 & 0 & \gamma_{1,5}\gamma_{1,6}\gamma_{1,7} \\ 0 & 0 & \gamma_{2,3}\gamma_{2,4} & 0 & \gamma_{2,6}\gamma_{2,7} \end{bmatrix} \begin{bmatrix} Age \\ Edu \\ Waterprice \\ Experience \\ Media \\ Time \\ Network \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \end{bmatrix} \end{aligned} \tag{6}$$

The following observations apply. First, in equation (4) for *Awareness* and *Perception* (which are unobservable and thus have no measurement scales) one coefficient is fixed at 1 (for *Aware1* and *Percep1*, respectively) to assign them measurement scales (hence, *Awareness* is measured in the scale of *Aware1* and *Perception* in the scale of *Percep1*).

Secondly, in equation (5) the latent variables are equal to their observed indicators (see section 4.3 for further details about the composition of the formative latent variables *Media* and *Network*). Consequently, the error terms in equation (5) are fixed at 0, since the latent variables have a one-to-one relationship with the corresponding observed variables.

3.4 Empirical results

In this section we first discuss data collection (the survey, section 4.1), present descriptive statistics (section 4.2) and discuss the estimated SEM, i.e. equations (4)-(6) (section 4.3).

3.4.1 The survey

The survey was carried out in the Guanzhong Plain, which is an arid to semi-arid region in Shaanxi Province, China. The sampling scheme was stratified random sampling. At the first stage, irrigation districts (ID) were selected, followed by the selection of canals within the selected IDs, villages per canal and finally farmers per canal.

In the Guanzhong Plain, irrigation is organized by irrigation districts (ID). Among the 100,000 IDs, the largest 8 account for 80% of total irrigated area. We only included the 8 largest in the sample because their irrigation infrastructure is more developed than in the other districts and because of their substantial area coverage.

Each of the 8 IDs has its own water source and is managed by an Irrigation Management Bureau. The number of canals varies per ID from 222 to 1806. Canals and villages were selected from all 8 IDs. In the second stage, a total of 37 canals were selected from the IDs as follows. First, per ID the number of canals was selected proportionally to its total. Secondly, since awareness and perception may vary by water availability, a canal was divided into an upstream and a downstream stratum[25]. From each stratum we selected 1 village, resulting in a total of 66 villages. Finally, we randomly selected 6-8 farmers per village, resulting in a total of 483 farmers. There were 37 (7.7%) questionnaires that could not be included in the analysis because of incomplete information. There was no evidence of any systematic non-response.

Data on socio-demographic and farming characteristics and on perception and awareness of water scarcity (Figure 3.1) was collected via face-to-face interviews using a

[25] Of the 37 canals, 8 irrigate only one village and thus have no upstream and downstream villages.

structured questionnaire (available at the first author's website). Prior to the interviews, a preliminary survey was conducted to test the draft questionnaire, i.e. to identify and, if necessary, to correct possible errors and clarify unclear questions.

Interviewers were selected from a group of Master and Ph.D. students majoring in agricultural economics or related subjects at Northwest A&F University, Shaanxi Province. Prior interview experience and understanding of the local language were two selection criteria. The interviewers were instructed and trained to familiarize them with the questionnaire and with communication with the farmers. This was done by going through all questions, one by one, explaining their meaning and possible answers. The face-to-face interviews were carried out in October of 2011 when harvest for the 2010/2011 cropping season was just finished.

3.4.2 Descriptive statistics

Table 3.1, 3.A.1 and 3.A.2 present descriptive statistics for the observed variables. From Table 3.1, it follows that the respondents' characteristics are in-line with population characteristics in the Guanzhong Plain (Aregay and Zhao, 2012).

Table 3.1 Descriptive statistics for the observed exogenous variables

Variables	Min.	Max.	Mean	S.D.
Age (years)	26	77	53.04	10.23
Edu (years)	0	12	6.67	1.81
Waterprice (Yuan/m^3)	0.02	1.16	0.33	0.14
Experience	1	5	2.74	1.49
Time	1	5	3.85	1.43

Note: *Edu* (education) is measured as years of schooling. *Experience* is measured by the response to the question "In the past, it was easy to get water when I irrigated my land." on a scale ranging from 1 (strongly disagree) to 5 (strongly agree), *Time* by the response to the question "How much of your working time do you spend on your farm?" on a 5-point scale: 1=0%-19%, 2=20-39%, 3=40-59%, 4=60-79%, 5=80%-100%.

Based on its definition in section 2, *Awareness* is measured by the following indicators: (i) understanding of the consequences of water scarcity (*Aware1*), (ii) the extent of mindfulness about water shortage (*Aware2*) and (iii) importance of water saving (*Aware3*). *Perception* is measured by four indicators: (i) knowledge of current water availability status (*Percep1*), (ii) knowledge of the change in the availability (*Percep2*) and quality (*Percep3*) of irrigation water (change was measured by asking the respondents to compare present and past water availability and quality), and (iv) expectation of water scarcity in the future (*Percep4*). Each of the indicators of *Awareness* and *Perception* is measured on a 5-point scale: strongly disagree, disagree, neither disagree nor agree, agree and strongly agree.

Table 3.A.1 shows a high level of awareness of irrigation water scarcity (Table 3.A.1, see appendix). 68% of the respondents report that water scarcity is hindering agricultural production while 61% express worry about irrigation water shortage. Only 6% is not concerned about water scarcity and thinks that water saving is not important. Regarding perception, a small percentage (17%) of the respondents strongly agree and another 20% agree that irrigation water is scarce in their villages. 57% think water availability is no worse than before. For irrigation water quality the percentage is lower at 46%. Regarding future irrigation water scarcity, 30% believes that the situation will worsen while 26% do not. We can thus conclude that, although most farmers do not perceive water as scarce yet, they are aware of water shortage. Note that farmers who are heedful (i.e. aware) of water scarcity are more likely to perceive water shortage. Particularly, only 47% of the respondents who think irrigation water is not scarce report worry about water shortage. However, among the farmers who believe that irrigation water is scarce, 83% state that they are worried.

The four indicators which measure *Network* include: (i) contact with other villagers (*Network1*), (ii) membership of water users' association (WUA) (*Network2*), (iii) relatives or neighbors who have adopted water-saving technologies (*Network3*), and (iv) contact with local government and irrigation managers (*Network4*). For *Network1*, a 5-point measurement scale ranging from "strongly disagree" to "strongly agree" was used. *Network2*, *Network3* and *Network4* are dichotomous variables taking the value 1 if "Yes", and 0 if "No". Since *Network* is a formative latent variable, the simplest way to measure it is to take the sum of the scores of the four indicators (Podsakoff et al., 2006). The latent variable *Media* is measured by (i) exposure to TV or radio (*Media1*), (ii) frequency of reading newspapers or books (*Media2*), (iii) frequency of Internet use (*Media3*) and (iv) exposure to slogans or propaganda about water saving (*Media4*). All four indicators are categorical variables taking the value 1 if the respondent replies "never", 2 "once or twice a week", 3 "three or four times a week", 4 "five to six times a week" and 5 "more than 7 times a week". *Media* score is the sum of the scores of the four indicators.

Table 3.A.2 displays the descriptive statistics for the two formative latent variables. The mean value (2.87) of *Network1* shows that the respondents quite often discuss water scarcity issues with each other. Furthermore, of the 446 farmers, only 8 (1.8%) are WUA members. Hence, the WUA participation rate is very low, in spite of the fact that WUA membership has been strongly advocated by the Irrigation Management Bureaus across

the Guanzhong Plain for long. Besides, only a small group of farmers reported that they know someone who is using water-saving technologies. Similar results were obtained for contact with local government and irrigation managers. For *Media*, watching television or listening to radio is the most prevalent form of media contact, followed by reading newspapers and using the Internet. Exposure to slogans or propaganda about water saving is low (mean 1.46).

3.4.3 The Estimated SEM

We estimated two models. Model 1 takes all indicators as measured on interval scales, calculates their covariance matrix and uses it to estimate model (4)-(6) by Maximum Likelihood. Model 2 takes into account that several of the observed variables are ordinal or discrete. It is estimated by Weighted Least Squares based on a matrix of polychoric correlations (Jöreskog and Sörbom, 2001). Note that Maximum Likelihood or Generalized Least Squares estimation on the basis of a covariance matrix or product-moment matrix in the case of ordinal or discrete scores, or mixtures of ordinal and interval scores, may lead to distorted parameter estimates, incorrect Chi-square goodness-of-fit measure and distorted standard errors (Jöreskog and Sörbom, 2001). Before going into detail, we observe that model (4)-(6) is identified because it meets the necessary and sufficient rank condition for a two-equation system (Greene, 2002).

Various measures exist to assess the goodness-of-fit of a SEM: χ^2, goodness of fit index (GFI), adjusted goodness of fit index (AGFI), comparative fit index (CFI), normed fit index (NFI) and the root mean square error of approximation (RMSEA). However, there are no widely accepted cut-offs for these goodness-of-fit indices (Hooper et al., 2008). The χ^2 reflects the distance between the sample covariance matrix and the theoretical covariance matrix based on the hypothesized model. Loosely speaking, the higher the p-value of the χ^2, the better the overall goodness-of-fit. Table 3.B.1 shows that the χ^2(df=52) for Model 1 is 89.58 and for Model 2 201.55 indicating a weak goodness-of-fit for the first model and a poor fit for the second. However, Hox and Bechger (1998) argue that the χ^2 statistic is sensitive to deviation from normality and large sample size (more than 400 which is the case in this study) which usually result in low p-values. A preferable measure in that case is the RMSEA. A RMSEA value < 0.08 indicates a reasonable fit. Table 3.B.1 shows that Model 1 meets this criterion whereas Model 2 is a border case. The alternative indices of both models (NFI=0.940, NNFI=0.953, CFI=0.973, GFI=0.972, AGFI=0.944) for Model 1 and (NFI=0.879, NNFI=0.833, CFI=0.905, GFI=0.939, AGFI=0.877) also indicate that Model 1 performs slightly better than Model 2. Because their goodness of fit measures differ only slightly, we present the estimation results for both models below.

We now turn to the estimated measurement models and the structural model. Before going into detail, we point out that the estimated coefficients are standardized (beta) coefficients. Hence, the scales of the regressors are irrelevant, and the explanatory variables are on equal footing. Specifically, a given coefficient measures the standard deviation change in the dependent variable due to a standard deviation increase in the corresponding explanatory variable. Note that standardization affects the coefficients of *Aware1* and *Percep1* that were fixed (at 1) to assign measurement scales to the latent variables *Awareness* and *Perception* to render the model identified.

Table 3.2 shows that all factor loadings in both Model 1 and Model 2 are highly significant. In addition, the coefficients in Model 2 are substantially above the recommended minimum level of 0.20 (Jöreskog and Sörbom, 2001). The interpretation of the loadings is as follows. A standard deviation increase in a latent variable, say *Awareness* in Model 1, leads to *inter alia* a 0.770 standard deviation increase in *Aware1* and a 0.993 standard deviation increase in *Aware2*. (Note that there is no z value for the coefficients of *Aware1* and *Percep1* because these coefficients were fixed). From Table 3.2 it follows that *Aware1* and *Aware2* are the most important indicators of *Awareness* while *Aware3* is a weak indicator in Model 1 (but not in Model 2). The reliabilities (R^2) of the indicators in Model 2 are higher than in Model 1. This applies in particular to indicator 3 whose reliability is only 0.021 in Model 1. For *Perception*, in both models *Percep1*, *Percep2* and *Percep4* are the most important indicators with satisfactory reliabilities while *Percep3* is the weakest indicator with very low reliability.

Table 3.2 The measurement models (standardized coefficients)

Latent variable	Indicators	Model 1			Model 2		
		Coefficient	S.E.	R^2	Coefficient	S.E.	R^2
Awareness	*Aware1*	0.770	---	0.344	0.583	---	0.340
	Aware2	0.993^{***}	0.110	0.408	0.679^{***}	0.069	0.461
	Aware3	0.092^{***}	0.035	0.021	0.483^{***}	0.062	0.233
Perception	*Percep1*	1.216	---	0.651	0.842	---	0.710
	Percep2	0.664^{***}	0.068	0.256	0.496^{***}	0.049	0.246
	Percep3	0.321^{***}	0.062	0.072	0.278^{***}	0.050	0.077
	Percep4	0.509^{***}	0.057	0.215	0.470^{***}	0.049	0.221

Note: ***p<.01.

Table 3.3 presents the structural models. The R^2s indicate a satisfactory fit for Model 1 and a good fit for Model 2. Globally speaking, the coefficients in both models are in line in terms of sign, significance and size. However, *Waterprice* is significant in Model 2 but not in Model 1. Below we only discuss Model 2.

As hypothesized in the conceptual model, *Awareness* and *Perception* strongly interact indicating that perception of irrigation water scarcity is a prerequisite for growing aware and, vice versa, that awareness promotes and facilitates perception.

Table 3.3 Standardized coefficients of the structural *Awareness-Perception* models

Variables	Model 1		Model 2	
	Awareness	*Perception*	*Awareness*	*Perception*
Perception	0.530(0.079)***	---	0.464(0.066)***	---
Awareness	---	0.275(0.152)*	---	0.231(0.114)**
Age	-0.099(0.052)*	---	-0.134(0.048)***	---
Edu	-0.063(0.053)	---	0.037(0.045)	---
Time	0.115(0.055)**	-0.022(0.043)	0.141(0.051)***	0.010(0.037)
Media	-0.010(0.049)	---	-0.005(0.048)	---
Waterprice	---	0.057(0.039)	---	0.066(0.033)**
Network	0.426(0.062)***	-0.029(0.086)	0.488(0.059)***	-0.040(0.072)
Experience	---	0.644(0.070)***	---	0.723(0.055)***
R^2	0.590	0.650	0.619	0.730

Note: Standard errors in parenthesis.
*p<.10, **p<.05, ***p<.01.

Regarding the exogenous variables, *Age* negatively and significantly affects *Awareness*. The coefficient of -0.134 supports the hypothesis that older farmers are less heedful about water shortage than their younger peers. In contrast to expectation, the impact of *Edu* on *Awareness* is insignificant, although the coefficient has the right (positive) sign. The impact of *Time* on *Awareness* is positive and significant, indicating that the more time a farmer spends on his farm, the more aware he(she) is of water scarcity. Its impact on *Perception*, however, is negligible and insignificant. An unexpected relationship is found for *Media* and *Awareness*, suggesting that access to media does not stimulate awareness of water scarcity. This result is probably due to low exposure to *Media2-Media4* (see Table 3.A.2) or to the fact that the media pays little attention to irrigation water scarcity. *Waterprice* has a small, though significant, impact on *Perception*. *Network* impacts positively and significantly on *Awareness* while its linkage to *Perception* is not statistically significant. Finally, *Experience* is the most important determinant of *Perception*, followed by *Awareness*.

Table 3.4 shows the standardized indirect and total effects on *Awareness* and *Perception* associated with each variable in Model 2. The total effect is the sum of the direct and indirect effects of a given variable. A direct effect is the effect from a causal variable on an endogenous impact variable, as given by its coefficient in Table 3.3. An indirect effect, on the other hand, refers to the effect of a variable on an endogenous variable via intervening endogenous variables for example via *Awareness* on *Perception* and, vice versa, via *Perception* on *Awareness*.

Table 3.4 Standardized total and indirect effects for Model 2

Variables	Indirect effects		Total Effects	
	Awareness	*Perception*	*Awareness*	*Perception*
Perception	0.056(0.030)*	0.120(0.063)*	0.520(0.079)***	0.259(0.137)*
Awareness	0.120(0.063)*	0.028(0.028)	0.120(0.063)*	0.374(0.205)*
Age	-0.016(0.009)*	-0.035(0.021)*	-0.150(0.052)***	-0.035(0.021)*
Edu	0.004(0.005)	0.010(0.013)	0.041(0.050)	0.010(0.013)
Time	0.022(0.018)	0.038(0.022)*	0.164(0.053)***	0.048(0.038)
Media	0.001(0.010)	-0.001(0.010)	-0.005(0.048)	-0.001(0.010)
Waterprice	0.034(0.018)*	0.008(0.006)	0.034(0.018)*	0.074(0.037)**
Network	0.038(0.019)**	0.122(0.062)**	0.526(0.061)***	0.081(0.038)**
Experience	0.376(0.055)***	0.087(0.041)**	0.376(0.055)***	0.810(0.040)***

Note: Standard errors in parenthesis.
*p<.10, **p<.05, ***p<.01.

The variable with the largest effect on *Awareness* is *Network* with a total effect of 0.526, followed by *Perception* and *Experience* with total effects of 0.520 and 0.376, respectively. Note that although there is no direct causal relationship, the impact of *Experience* on *Awareness* is significant, via *Perception*. *Time* and *Waterprice* have small but significant impacts on *Awareness* with total effects of 0.164 and 0.034, respectively. Finally, *Age* has a negative effect on *Awareness*.

In line with expectations, *Experience* and *Awareness* are the two most influential variables for *Perception* with total effects of 0.810 and 0.374, respectively. *Network* and *Waterprice* influence *Perception* indirectly with total effects of 0.081 and 0.074, respectively. Finally, *Edu*, *Time* and *Media* have weak and insignificant total effects on *Perception*.

3.5 Summary and conclusions

In this paper we have analyzed the influence of farming characteristics, socio-demographic and psychological factors on farmers' awareness and perception of irrigation water scarcity, based on a cross-sectional dataset of 446 farmers from the Guanzhong Plain, Shaanxi Province, China. Structural equation modeling has been applied to estimate the conceptual model based on a brief literature review. The main results and their policy implications are the following.

The farmers in the sample are strongly aware of irrigation water scarcity, although a minority of 37% actually perceives scarcity in their villages. For awareness the figure is substantially higher: 61% stated that they were worried about water shortage. Meanwhile, farmers who were heedful about water scarcity were more likely to perceive water scarcity than those who were not.

Personal contact is more important than mass media exposure in shaping perception and awareness. The more connected he (she) is to social networks with knowledge of water scarcity, the larger the possibility that a farmer will perceive irrigation water as scarce and think that water saving is important. This finding is consistent with Scherer and Cho's (2003) assertion that information related to hazard perception is shared through social linkages in the first place. The finding has the important policy implication that changing behavior, such as improving irrigation water use efficiency, should be stimulated by way of spreading information via social networks in the first place. Of special importance in this regard are key informants who can influence the opinion, awareness and perception in their networks and thus the behavior of individual farmers.

The positive effect on awareness of time spent on farming is important because an increasing number of Chinese farmers are part-time farmers who spend a substantial proportion of their time in urbanized areas. Due to poor awareness, these part-time farmers may fail to improve irrigation water use efficiency and related agricultural practices. They need to be made aware of water scarcity problems via their networks in the first place.

A higher water price generates a higher level of perception and, through perception, a higher level of awareness. However, the present price of irrigation water is far below its marginal value because of the deliberate Chinese policy to keep water price low to increase farmers' income (Lohmar et al., 2003). This policy should be revised. The price of irrigation water should reflect its marginal value and be used as a policy handle to signal its scarcity in a bid to improve irrigation water use efficiency.

Finally, further research on awareness and linked agricultural practices, including adoption of water-saving technologies, is urgently needed in Northwest China. The reason is that water scarcity is an urgent and pressing problem in the area, with far reaching environmental impacts and threats to food security and socio-economic development in the whole of China.

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Appendix 3.A Summary statistics for latent variables

Table 3.A.1 Frequency distribution of the indicators of *Awareness* and *Perception*

Indicators	Questions	Strongly	Disagree	Neither	Agree	Strongly	Mean	S.D.
Aware1	Irrigation water scarcity is hindering agriculture production.	3.81	22.42	5.38	23.09	45.29	3.84	1.31
Aware2	I always worry about irrigation water shortage.	17.49	19.96	1.35	25.34	35.87	3.42	1.55
Aware3	Saving irrigation water is important.	3.36	2.24	0.90	12.78	80.72	4.65	0.89
Percep1	Irrigation water is scarce in my village.	30.04	32.06	1.35	19.51	17.04	2.61	1.50
Percep2	Irrigation water scarcity now is worse than before.	15.25	41.48	9.64	19.96	13.68	2.75	1.31
Percep3	The quality of irrigation water now is worse than before.	11.88	34.30	25.11	16.59	12.11	2.83	1.20
Percep4	Irrigation water will be scarcer in the next two years than it is now.	7.85	18.16	44.39	15.70	13.90	3.10	1.10

Table 3.A.2 Indicators for the latent variables *Network* and *Media*

Indicators	Questions	Min.	Max.	Mean	S.D.
Network1	I often discuss water scarcity issues with other villagers.	1	5	2.87	1.36
Network2	I am a member of water users' association (WUA).	1	2	1.02	0.13
Network3	I have relatives or neighbors who are using water saving technologies.	1	2	1.11	0.31
Network4	I have relationships with local government and irrigation managers.	1	2	1.20	0.40
Media1	How many times a week do you watch TV or do you listen to the radio?	1	5	4.68	0.82
Media2	How many times a week do you read newspapers or books?	1	5	1.71	1.25
Media3	How many times a week do you surf the internet?	1	5	1.17	0.74
Media4	How many times a year do you see slogans or propagandas about irrigation water saving?	1	5	1.46	1.04

Appendix 3.B Goodness-of-fit statistics

Table 3.B.1 Goodness-of-fit statistics of Model 1 and Model 2

	χ^2	NFI	NNFI	CFI	GFI	AGFI	RMSEA
Model 1	89.58(df=52, p=0.001)	0.940	0.953	0.973	0.972	0.944	0.040
Model 2	201.55(df=52, p=0.000)	0.879	0.833	0.905	0.939	0.877	0.080

Chapter 4

Technical and allocative efficiency of irrigation water use in the Guanzhong Plain, China[26]

Abstract: Due to increasing water scarcity, accelerating industrialization and urbanization, efficiency of irrigation water use in Northern China needs urgent improvement. Based on a sample of 347 wheat growers in the Guanzhong Plain, this paper simultaneously estimates a production function, and its corresponding first-order conditions for cost minimization, to analyze efficiency of irrigation water use. The main findings are that average technical, allocative, and overall economic efficiency are 0.35, 0.86 and 0.80, respectively. In a second stage analysis, we find that farmers' perception of water scarcity, water price and irrigation infrastructure increase irrigation water allocative efficiency, while land fragmentation decreases it. We also show that farmers' income loss due to higher water prices can be offset by increasing irrigation water use efficiency.

JEL classification: Q15 Q25 Q12 D24

Keywords: Irrigation water, Technical efficiency, Allocative efficiency, Economic efficiency, Perception of water scarcity, Structural equation modeling

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4.1 Introduction

Due to water scarcity, irrigation plays an important role in agricultural production in North China. Huang et al. (2006) points out that widespread irrigation is required to keep up and expand agricultural outputs, particularly wheat and maize, but also to alleviate poverty. However, water scarcity in the region has been worsening due to accelerating industrialization and urbanization, but also because of environmental challenges, such as climate change and water pollution (Jiang, 2009). These developments have led to increased competition among the main water users, i.e. agriculture, industry and households.

Irrigation consumes 60% of total annual water resources in *inter alia* the Guanzhong Plain, which is a region facing severe and increasing water scarcity. In the area, 75% of grain production comes from irrigated land which accounts for 50% of total arable land. Expansion of grain production, and thus of irrigation, is needed to feed China's large and still growing population. However, water has higher marginal returns in industry and the residential sector. Under such circumstances, it is imperative for agriculture to improve its water use efficiency (Lybbert and Sumner, 2012).

This goal of the paper is to measure the efficiency of farmers' irrigation water use and identify its determinants, based on a sample of 347 farmers in the Guanzhong Plain. The paper contributes to the literature in the following three aspects. First, it focuses on both technical and allocative efficiency. Water use efficiency is commonly defined as yield per m^3 water. See, for instance, Wang et al. (2010). This measure is biased and inappropriate, however, because it ignores the fact that yield is not produced by a single input, water, but by multiple inputs including water, but also fertilizers, seeds, machinery and labor. Several researches have recognized this and analyzed technical efficiency of irrigation water use, while controlling for the contributions of all other inputs (Karagiannis et al., 2003; Speelman et al., 2009, among others). For instance, based on data on 50 vegetable farms in Greece, Karagiannis et al. (2003) analyzed input-specific technical efficiency as a measure of water use efficiency. However, technical efficiency analysis does not measure a farmer's ability to allocate irrigation water and other inputs to their cost-minimizing input proportions. For that purpose, allocative efficiency analysis is needed. To the best of our knowledge, there are no analyses of allocative efficiency of irrigation water use. This paper fills this gap by simultaneously estimating a production function, and its corresponding first-order conditions for cost minimization, to measure this latter kind of efficiency. In addition, it measures technical and economic efficiency.

Secondly, in a bid to get insight into the determinants of technical and allocative efficiency, the paper does not only consider farm-specific characteristics, like farm size, and socioeconomic features, such as farmer's age and education, but also a farmer's perception of water scarcity. As argued by Folmer (2009) and Folmer and Stenman (2011), ignoring the latter kind of variables leads to model under-specification, and thus to biased estimators of the coefficients of the standard explanatory variables, like farm and farmer characteristics, and to invalid inference. Furthermore, if perception turns out to be a determinant of efficiency, it is a potential policy handle in that improving perception via e.g. extension, may induce farmers to reduce their water use. (Note that the literature has so far paid little attention to perception of water scarcity and its potential as a policy instrument.)

Thirdly, the paper provides support to water pricing as a policy handle. In China, the use of this policy instrument is still under debate. Huang et al. (2010) argues that the price of irrigation water in China is too low to induce farmers to save water. However, policymakers fear that higher prices will jeopardize farmers' income and further widen the gap between rural and urban residents (Lohmar et al., 2007). Little research has been conducted to quantify the effect of water price on income. We test whether the income loss due to higher irrigation water price can be offset by more efficient use of water.

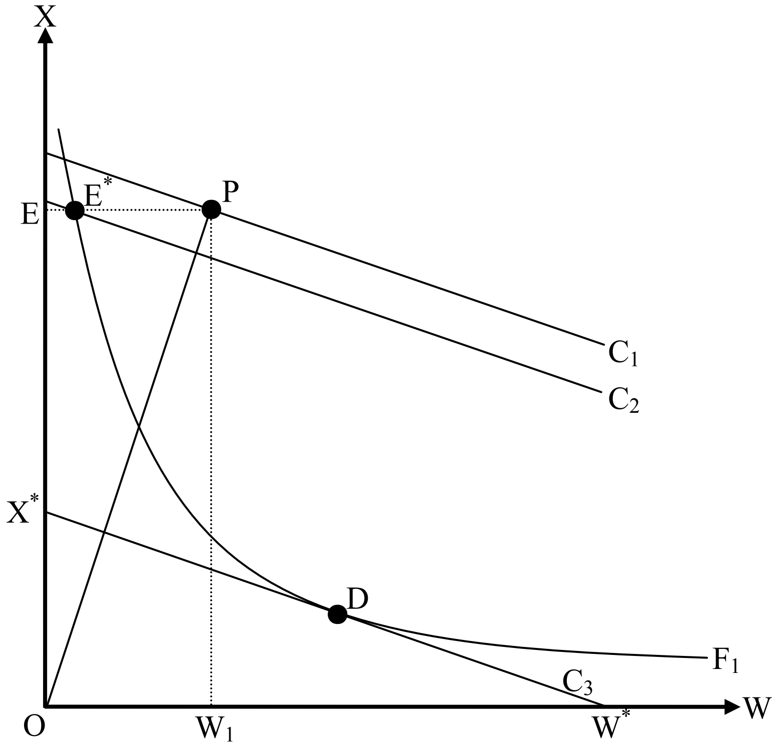
The structure of the paper is as follows. Section 4.2 presents the methodological framework. Sections 4.3 and 4.4 discuss the data and the empirical results. Section 4.5 presents the conclusions and policy recommendations.

4.2 Methodology

4.2.1 Single-factor technical, allocative and economic efficiency

Since Farrell's (1957) pioneering work, the three efficiency measures technical, allocative and economic efficiency, have been extensively used to assess economic performance of various economic sectors. This also applies to agriculture, where a substantial literature on efficiency of agricultural production has developed. Few studies, however, focus on efficiency of a particular input, such as water. To gain insight into the efficiency of the single input irrigation water, we present in this section the notions of *single-factor* *technical efficiency* (*SFTE*), *single-factor allocative efficiency* (*SFAE*) and *multi-factor economic efficiency* (*MFEE*). These concepts, as introduced by Kopp (1981) and Kopp and Diewert (1982), are illustrated in Figure 4.1.

Figure 4.1 Single-factor technical, allocative and multi-factor economic efficiency



Note: Figure 4.1 is based on Kopp (1981) and Reinhard (1999).

In Figure 4.1, there is a single output, *Y*, and two inputs *W*, i.e. irrigation water, and *X*, which denotes all other inputs, such as capital, labor, fertilizers and so on. F_1 is an isoquant which represents the production frontier at which a technically, perfectly efficient farmer uses least inputs to produce a given output. Point *P* is above the production frontier indicating that the farmer who produces at that point is technically inefficient.

Consider the isocost lines C_1, C_2 and C_3. Point *P* at C_1 is the actual cost at which the producer uses OW_1 of input factor *W* and *OE* of input factor *X*. Point E^* on C_2 denotes the cost where the use of *W* is technically efficient, given *X* (*OE*) and output. The isocost line C_3 is drawn tangent to the isoquant F_1 at point *D* where *W* and *X* are both allocatively efficient. The slope of C_3 (with negative sign) equals the ratio of the prices of *W* and *X*.

X^* and W^* are intersections[27] of the isocost line C_3 and the vertical and horizontal axis, respectively. C_3 is the cost at point *D*.

EE^* is the minimum feasible use of *W* conditional on a given level of input *X* (*OE*) and actual output. *SFTE* of *W* at point *P* equals EE^*/EP. From a cost perspective, single-factor technical cost efficiency (*SFTCE*) of *W* is the ratio between the cost when *W* is technically efficient and actual cost, that is, C_2/C_1. *SFAE* of *W* is the ratio between the cost at point *D* and the cost at point E^*, that is, C_3/C_2. Finally, *MFEE* is the product of *SFTCE* and *SFAE* and equals C_3/C_1. Since *MFEE* is determined as their product, the focus below will be on *SFTE* and *SFAE*. Below we label the three types of single factor irrigation water efficiencies as *IWTE*, *IWAE* and *MFEE*, respectively.

4.2.2 Measurement of irrigation water technical efficiency (IWTE)

Having introduced the concepts of *SFTE* and *SFAE* in the previous section, we now turn to the methodology of estimating these measures. In this subsection we pay attention to *SFTE*, in the next to *SFAE*.

Following Aigner et al. (1977), the general stochastic production function for cross sectional data is:

$$Y_i = F(X_i;\beta)\exp(v_i - u_i) \tag{1}$$

For farmer *i*, production function (1) describes output Y_i as a function of a vector of inputs X_i and an error term made up of two components: $v_i \sim N(0,\sigma_v^2)$, representing the standard error term, and the non-negative error term u_i, which follows a half-normal distribution, reflecting the shortfall of a farmer's output from the production frontier, due to technical inefficiency.

A translog stochastic frontier production function is usually chosen for (1). For the *i*th farmer, the translog stochastic frontier production function with 4 inputs, reads:

$$\begin{aligned} lny_i = \beta_0 + \beta_w lnw_i + \sum_{j=1}^{3}\beta_j lnx_{ji} + \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3}\beta_{jk} lnx_{ji} lnx_{ki} \\ + \textstyle\sum_{j=1}^{3}\beta_{wj}\, lnw_i lnx_{ji} + \frac{1}{2}\beta_{ww}(lnw_i)^2 + v_i - u_i \end{aligned} \tag{2}$$

---

[27] X^* is the quantity of *X* when cost (C_3) is incurred to purchase *X* only, while W^* is the quantity of *W* when cost (C_3) is incurred to purchase *W* only.

where y_i is output (wheat in the present study). The 4 inputs considered in the application below include: (1) x_{1i}, the sown area (*Land*); (2) x_{2i}, *Labor*; (3) x_{3i}, *Other inputs*; and (4) w_i, *Water*.

Following Schmidt and Lovell (1979), the first-order conditions of cost minimization imply that the technical rate of substitution equals the factor price ratio. To avoid identification problems, we arbitrarily choose *w* as numeraire. For farmer *i*, the first-order conditions are:

$$lnS_{ji} - lnS_{wi} - \ln(p_{ji}x_{ji}) + \ln(p_{wi}w_i) = \tau_{ji} \quad j\text{=1,2,3} \tag{3}$$

where

$$S_{ji} = \beta_j + \sum_k \beta_{jk} lnx_{ji} + \beta_{wj} lnw_i, \; j\text{=}\textit{Land}, \textit{Labor} \text{ and } \textit{Other inputs} \tag{4}$$

In (3), p_{ji} is the price of the *j*th input, p_{wi} is the price of water and S_{ji} is the partial derivative (elasticity) with respect to input *j*. τ_{ji} is the error term which is normally distribute and can take both positive and negative values. (Note that τ_{ji} also corresponds to allocative inefficiency which is defined as the extent of failure to choose cost-minimizing factor proportions between the input *j* and the numeraire *w*. For further details, see section 2.3.) If τ_{ji}>1, input x_i is underutilized relative to irrigation water; it is overutilized, if τ_{ji}<1.

Following Reinhard et al (1999), *IWTE* for farmer *i* can be obtained by setting actual production equal to production under no technical inefficiency ($u_i = 0$), i.e. when using minimum feasible irrigation water w_i^F while producing the same level of output (y_i).

$$F(x_i, w_i^F; \beta) \exp(v_i) = F(x_i, w_i; \beta) \exp(v_i - u_i) \tag{5}$$

From (5), *IWTE* for individual farmer *i* can be obtained as:[28]

$$IWTE_i = exp\left(\frac{-\varpi_i \pm \sqrt{\varpi_i^2 - 2\beta_{ww}u_i}}{\beta_{ww}}\right) \tag{6}$$

where $\varpi_i = \beta_w + \sum_{j=1}^{3} \beta_{wj} lnx_{ji} + \beta_{ww} lnw_i$ (7)

[28] For details, see Reinhard et al. (1999) and Tang et al. (2013a).

4.2.3 Measurement of irrigation water allocative efficiency (IWAE)

We now turn to *IWAE*, i.e. irrigation water allocative efficiency when all inputs are adjusted to their respective cost-minimizing input proportions, given prices of all inputs, and output. As shown in section 2.1, allocative efficiency of irrigation water is the ratio between the cost at point E^* (C_2 in Figure 1) and the cost at point D (C_3 in Figure 1). Suppressing the subscript i, we have for C_2

$$C_2 = P_w w^F + \sum_{j=1}^{3} p_j x_j \tag{8}$$

At point D in Fig.1 the producer is both technically and allocatively efficient. Hence, the minimum feasible cost of producing actual output Y at point D, $C^*(p, y)$, is:

$$C^*(p, y) = P_w w^* + \sum_{j=1}^{3} p_j x_j^* \tag{9}$$

The optimal inputs x_j^* and w^* are obtained by solving the equations (2) and (3) with the allocative inefficiency term τ_{ji}=0, and the technical inefficiency term u_i=0.[29]

Finally, from its definition *IWAE* is

$$IWAE = \frac{C^*(p,y)}{C_2} \tag{10}$$

Finally, from its definition, *MFEE* is obtained as:

$$MFEE = IWTCE * IWAE \tag{11}$$

where $IWTCE = C_2/C_1$.[30]

4.3 The conceptual model and the structural equation model (SEM)

Below we first develop the conceptual model (Figure 4.2), i.e. the model that describes the determinants of *IWTE* and *IWAE* (section 4.3.1). Next, in section 4.3.2, we present it as a Structural Equation Model (SEM).

4.3.1 The determinants of IWTE and IWAE

The scores for *IWTE* and *IWAE* are obtained from the equations (6) and (10) in section 2. We assume that the explanatory variables discussed below apply to each of the two types

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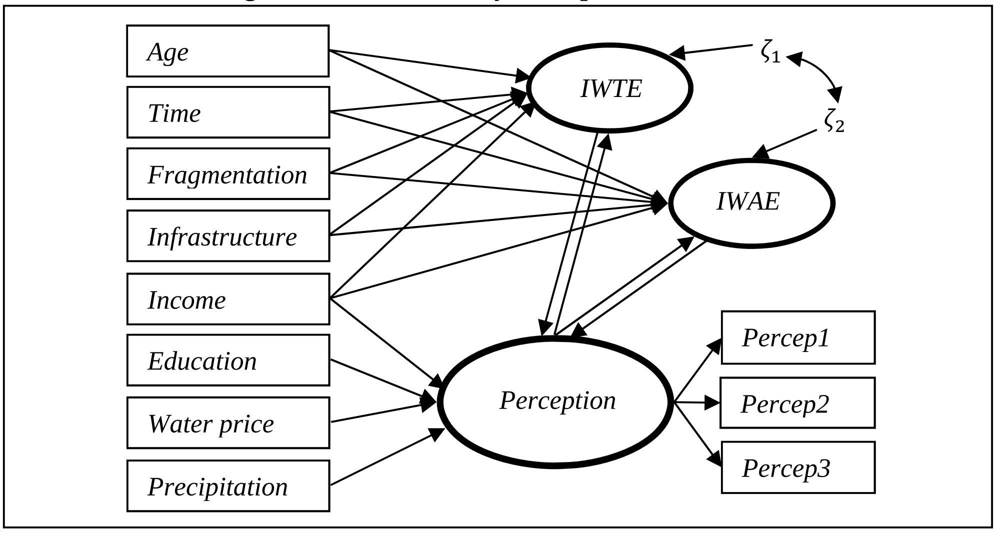
[29] Equations (2) and (3) make up a system of 4 nonlinear equations in 4 unknowns x_j^*. We solved them using Matlab by setting the actual values as starting values (Rodriguez- Alvarez et al., 2004).

[30] Here C_1 is the actual cost.

of efficiencies, though possibly with different coefficients. Therefore, we use the catch-all label *Efficiency* in this section.

Figure 4.2 The Efficiency-Perception Model[31]



4.3.1.1 Endogenous explanatory variables

As an explanatory variable of both types of efficiency, we postulate Perception of water scarcity (*Perception*). This assumption is based on the growing evidence that economic behavior is strongly influenced by psychological factors including perceptions, expectations and habits (Folmer (2009), Folmer and Johansson-Stenman (2011) and the reference therein). The underlying mechanism is that perception increases intrinsic motivation which enhances environmentally friendly behavior (Lindenberg, 2001).

We take *Perception* as a latent variable or theoretical construct, i.e. a variable that refers to a phenomenon that is supposed to exist but cannot be directly observed (see e.g. Folmer (1984) and the references therein).[32] We measure the latent variable *Perception* by the following three items (observed variables), each measured at a 5 points scale:[33]

(i) *Perception 1* (*Percep1*): Irrigation water is scarce in my village.
(ii) *Perception 2* (*Percep2*): Irrigation water scarcity is worse now than before.
(iii) *Perception 3* (*Percep3*): Irrigation water will be scarcer in the next two years than it is now.

[31] Error terms not included.
[32] See section 4.3.2 for the econometrics of handling latent and observed variables.
[33] Each item is presented as a statement with response categories ranging from fully disagree to fully agree.

We expect a positive impact of *Perception* on *Efficiency*. This expectation is based on the assumption that farmers who clearly perceive water as a scarce input are likely to be intrinsically motivated to be efficient.

We do not only hypothesize an impact of *Perception* on *Efficiency*, but also vice versa. That is, we assume that efficient farmers perceive water scarcity less as a problem. We have not been able to find evidence for this hypothesis in the social science and economics literature. However, experts on irrigation in the Guanzhong Plain have pointed out in various in-depth interviews that efficient farmers have a more optimistic view on water scarcity (as measured by the above three observed variables) than less efficient farmers. Therefore, we test this hypothesis in the empirical analysis below.

4.3.1.2 Exogenous variables

We first discuss the exogenous explanatory variables of *Efficiency* and next those of *Perception*.

Age. Chen et al. (2009) shows that older farmers are more technically efficient than younger farmers. The explanation is that older farmers have more farming experience and thus have developed more efficient irrigation practices. Hence, we expect a positive effect on *Efficiency*.

Time spent on farming (*Time*). In the Guanzhong Plain, there is a growing number of part-time farmers who spend less time on irrigation; particularly they irrigate less frequently than their full time peers. This restriction reduces the possibilities for “precise irrigation” (right moment and adequate amount). Moreover, since they have off-farm income, farming activities, including irrigation, are likely to be less important to them than to full time farmers. Hence, we assume that part-time farmers are less efficient than their full time peers.

Land Fragmentation (*Fragmentation*). This variable is measured by the number of different plots a farmer cultivates. A large number of different plots indicates a high level of land fragmentation. The impact of land fragmentation on efficiency of agricultural production in general has been empirically investigated in China. Based on a sample of 1093 rice producers in South-east China, Tan et al. (2010) showed that land fragmentation is an important, negative, determinant of technical efficiency. For 339 rice producers in Zhejiang, Hubei, and Yunnan Provinces, Zhang et al. (2011) found that land fragmentation is hindering technical efficiency. To the best of our knowledge, the impact on irrigation water efficiency has not been investigated yet. We hypothesize that land fragmentation decreases *Efficiency*.

Irrigation infrastructure (*Infrastructure*). At the termination of the collective agricultural system in 1978, irrigation canals started to deteriorate due to reduced maintenance which, *inter alia,* has led to seepage (Wang et al., 2006).[34] In 1999, the World Bank started an irrigation infrastructure repair project in the Guanzhong Plain. However, not all canals have been repaired and presently there exist differences in irrigation infrastructure quality. We expect farmers located at repaired (cement) canals to be more efficient. Infrastructure takes the value 1 if the farmer is connected to a cement irrigation canal and 0 otherwise.

Income. Yu et al. (2008) found a positive impact of net per capita income on water-saving technology adoption in 10 provinces in China. The explanation is that possibilities to purchase and use more advanced technology increase with income. We thus assume a positive impact on *Efficiency*.

We now turn to the exogenous explanatory variables of *Perception*.

Income. We also hypothesize a positive income effect on *Perception* in that higher income allows the acquisition of information which in its turn may promote clearer perception.

Education. Education is measured as years of schooling in this study. We assume that educated farmers have clearer perceptions of irrigation water scarcity than uneducated because education makes individuals more knowledgeable and able to interpret a complex phenomenon like the environment (Stapp, 1969). We hypothesize a positive impact on *Perception*.

Water price. Irrigation water price varies in the Guanzhong Plain, mainly because of scarcity. Wang et al. (2009) found that farmers respond to higher water prices by reducing water use. The reason is that water price signals the value of water. We therefore expect *Water price* to have a positive impact on *Perception*.

Precipitation. People form perceptions of their environment via signals and stimuli that they receive from it (Sudarmadi et al., 2001). In the case of irrigation water,

[34] In the Guanzhong Plain, a canal is used by a group of farmers. Irrigation water flows from the canal to the farmlands. Farmers are charged for the total amount of water withdrawn, including water lost during transportation due to seepage. If a canal is totally destroyed, the farmers who use it, have no longer access to irrigation water.

Precipitation is an important signal. In the study area, precipitation, ranges from 137mm to 220mm during the growing season (from October to May). We hypothesize that *Perception* varies inversely with *Precipitation* in that in areas with more rainfall perception of water scarcity is lower.

4.3.2 SEM

The conceptual model above contains the latent variable *Perception* as well as several observed variables including the indicators that measure *Perception*. Both types of variables can be simultaneously handled by means of a structural equation model (SEM). A SEM consists of two sub-models: two measurement models (equations 11 and 12) and a structural model (equation 13) (Jöreskog 1977; Jöreskog and Sörbom, 2001). The measurement model specifies the relationship between the latent variables and their observed indicators[35] while the structural model represents the relationships between the latent exogenous and latent endogenous variables as well as the relationships among the latent endogenous variables. Specifically:

$$\mathrm{y} = \Lambda_y \eta + \varepsilon \tag{11}$$

$$\mathrm{x} = \Lambda_x \xi + \delta \tag{12}$$

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta \tag{13}$$

where y is a $\mathrm{p} \times 1$ vector of endogenous observed variables, x a $\mathrm{q} \times 1$ vector of exogenous observed variables, η an $\mathrm{m} \times 1$ vector of latent endogenous variables, and ξ a $\mathrm{n} \times 1$ vector of latent exogenous variables. Λ_y and Λ_x are $\mathrm{p} \times \mathrm{m}$ and $\mathrm{q} \times \mathrm{n}$ matrices of regression coefficients or loadings. B is an $\mathrm{m} \times \mathrm{m}$ matrix with β_{ij} representing the effect of the jth endogenous latent variable on the ith endogenous latent variable, and Γ is an $\mathrm{m} \times \mathrm{n}$ matrix with γ_{ij} representing the effect of the jth exogenous latent variable on the ith endogenous latent variable. Finally, ε and δ are $\mathrm{p} \times 1$ and $\mathrm{q} \times 1$ vectors of measurement errors of y and x, with covariance matrices θ_ε and θ_δ, respectively. ζ is a vector of disturbances of the structural model. Its covariance matrix is Ψ. For identification, estimation, testing and modification indices we refer to Jöreskog and Sörbom (2001). Folmer and Oud (2008) discuss the theoretical and empirical advantages of using SEM.

[35] Note that directly observed variables can be conveniently handled in the SEM framework by specifying an identity relationship in the measurement model between the latent variable and the corresponding observed variable.

In SEM notation the conceptual model presented in Figure 4.2 reads:

$$\begin{bmatrix} IWTE \\ IWAE \\ Percep1 \\ Percep2 \\ Percep3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \lambda_{3,1} \\ 0 & 0 & \lambda_{4,1} \\ 0 & 0 & \lambda_{5,1} \end{bmatrix} \begin{bmatrix} IWTE \\ IWAE \\ Perception \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{bmatrix} \tag{14}$$

$$\begin{bmatrix} Age \\ Time \\ Fragmentation \\ Infrastructure \\ Income \\ Education \\ Water\ price \\ Precipitation \end{bmatrix} = \begin{bmatrix} 10000000 \\ 01000000 \\ 00100000 \\ 00010000 \\ 00001000 \\ 00000100 \\ 00000010 \\ 00000001 \end{bmatrix} \begin{bmatrix} Age \\ Time \\ Fragmentation \\ Infrastructure \\ Income \\ Education \\ Water\ price \\ Precipitation \end{bmatrix} \tag{15}$$

$$\begin{bmatrix} IWTE \\ IWAE \\ Perception \end{bmatrix} = \begin{bmatrix} 0 & 0 & \beta_{1,3} \\ 0 & 0 & \beta_{2,3} \\ \beta_{3,1} & \beta_{3,2} & 0 \end{bmatrix} \begin{bmatrix} IWTE \\ IWAE \\ Perception \end{bmatrix}$$

$$+ \begin{bmatrix} \gamma_{1,1}\gamma_{1,2}\gamma_{1,3}\gamma_{1,4}\gamma_{1,5} & 0 & 0 & 0 \\ \gamma_{2,1}\gamma_{2,2}\gamma_{2,3}\gamma_{2,4}\gamma_{2,5} & 0 & 0 & 0 \\ 0 \quad 0 \quad 0 \quad 0 & \gamma_{3,5}\gamma_{3,6}\gamma_{3,7}\gamma_{3,8} \end{bmatrix} \begin{bmatrix} Age \\ Time \\ Fragmentation \\ Infrastructure \\ Income \\ Education \\ Water\ price \\ Precipitation \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \end{bmatrix} \tag{16}$$

$$\Psi = \begin{pmatrix} \psi_{11} & & \\ \psi_{21} & \psi_{22} & \\ & & \psi_{33} \end{pmatrix} \tag{17}$$

Equations (14) and (15) are the endogenous and exogenous measurement models, respectively, and equation (16) is the structural model. (17) is the covariance matrix of the vector of structural error terms ζ.

From the conceptual model presented in section 3.1, it follows that there may be some common factors influencing the disturbances of *IWTE* and *IWAE*. To account for this, we specify ψ_{21} as a free parameter that is to be estimated. (Note the similarity to Seemingly Unrelated Regressions (SUR)).

4.4 Empirical results

4.4.1 Data collection and descriptive statistics

The analysis is based on a cross-sectional dataset collected in a survey among 446 farmers in the Guanzhong Plain, for the crop year 2011, which runs from October 2010 to May 2011. Although virtually all farmers produce several crops, we only consider wheat farmers which is the main crop irrigated. Other crops such as corn and apple require no or little irrigation. *Output* is measured as yield of wheat times price.

The following multi-stage sampling procedure was applied. First, since irrigation in the Guanzhong Plain is organized by irrigation districts (ID), we sampled IDs at the first stage. Among the approximately 100,000 IDs, we chose the nine largest because of their well-structured irrigation infrastructure and substantial area coverage of approximately 80 percent. At the next stage, we sampled canals within the selected IDs. For each ID, we randomly sampled 2 to 12 canals proportional to its total number of canals. At the third stage, we sampled villages per canal. To account for differences in water availability between upstream and downstream areas, we randomly sampled 1 village from each stratum. The total number of villages sampled was 66. At the final stage, we randomly sampled 5-7 wheat farmers per village, resulting in 405 wheat farmers. Among them, 58 did not irrigate[36]; they were excluded from the sample which resulted in a sample of 347 farmers.

Face-to-face interviews were conducted by a group of interviewers consisting of Master and Ph.D students at Northwest A&F University majoring in agricultural economics. Before the interviews, a preliminary survey was held to test the structure of the questionnaire and the clarity of the questions. Based on the outcome of this survey, the ambiguous and unclear questions were revised. The interview was carried out in October, 2011 when the harvest was finished.

Data used in the stochastic frontier analysis include the quantity and price for each of the following inputs: (1) *Land* (measured in mu); (2) *Labor* (measured in man-days); (3) *Other inputs* (the sum of the monetary value of all other inputs including seeds, fertilizers, machinery and pesticides); and (4) *Water* (measured in m^3). Table 4.1 presents descriptive statistics for the key variables included in the analysis and Table 4.2 for the indicators of perception.

[36] The main reasons for the 58 farmers to abstain from irrigating are: (1) they are absent from the farm for most of the irrigation season; (2) they think there is no need for irrigation because rainfall is sufficient; (3) there is no irrigation infrastructure.

Table 4.1 Descriptive statistics

Variable	Unit of measurement	Min.	Max.	Mean	S.D.
Yield	kg	400	40000	5163	3640
Price of yield	Yuan/kg	0.75	1.50	1.01	0.05
Output	Yuan	400	38800	5209	3659
Land	mu	0.40	40.00	5.71	3.86
Labor	man-days	0.45	46.00	8.26	6.30
Water	m^3	38	9389	1535	1406
Other inputs	Yuan	157	20100	2156	1612
PriceLand	Price of land in Yuan/mu	40.00	1500.00	241.99	193.65
PriceLabor	Price of labor in Yuan/day	30.00	200.00	73.25	27.25
Age	Years	26	77	53.08	10.07
Education	Years	0	12	6.64	1.70
Income	Yuan	1000	195000	26941	25103
Time	---	1	5	3.80	1.44
Water price	Yuan/m^3	0.02	1.00	0.32	0.13
Fragmentation	---	1	15	2.74	1.75
Precipitation	mm	137	220	174.31	17.07
Infrastructure	---	0	1	0.52	0.49
IWTE	---	0.06	0.76	0.35	0.14
IWTCE	---	0.75	0.99	0.93	0.04
IWAE	---	0.64	0.98	0.86	0.07
MFEE	---	0.60	0.93	0.80	0.07

Source: The survey.

Table 4.2 Descriptive statistics for indicators of *Perception*

Indicators	Strongly disagree (%)	Disagree (%)	Neither disagree nor agree (%)	Agree (%)	Strongly agree (%)	In total
Percep1	30.55	31.99	1.44	18.16	17.87	100
Percep2	14.12	42.36	10.09	19.02	14.41	100
Percep3	7.78	17.87	44.96	17.29	12.10	100

Source: The survey.

4.4.2 The frontier model

The simultaneous equations (3) and (4) were estimated by the Stata program by Kumbhakar and Wang (2006). We first tested the Cobb-Douglas versus the translog production function. The difference of the log likelihood test statistics follows a χ^2_{10} distribution (Battese and Coelli 1995). We rejected the Cobb-Douglas specification at 1% significance level.[37]

The estimates of the translog model are reported in Table 4.3. Only 2 of the 14 variables (ln*Labor**ln*Water* and ln*Water**ln(*Other inputs*) are insignificant. The ratio

[37] The log likelihood for the Cobb-Douglas specification was -455.77 while for the translog specification it was -133.38. So the χ^2_{10} statistics is 322.39. The 1% significance level with 10 degrees of freedom is 23.21.

$\frac{\sigma_u^2}{\sigma_u^2+\sigma_v^2} = 44.79\%$ indicates that technical efficiency contributes 44.79% to the total variance of output.

Table 4.3 The estimated translog production function

Variable	Coefficient	S.E.
Constant	-8.0383***	0.9090
ln*Land*	-3.7634***	0.3023
ln*Labor*	0.4180***	0.1180
ln*Water*	0.3432***	0.0497
ln(*Other inputs*)	4.1463***	0.2881
ln*Land**ln*Land*	-0.7910***	0.0605
ln*Labor**ln*Labor*	-0.0601***	0.0089
ln*Water**ln*Water*	-0.0423***	0.0050
ln(*Other inputs*)*ln(*Other inputs*)	-0.6157***	0.0487
ln*Land**ln*Labor*	0.0955***	0.0139
ln*Land**ln*Water*	0.0375***	0.0052
ln*Land**ln(*Other inputs*)	0.6696***	0.0529
ln*Labor**ln*Water*	0.0073	0.0072
ln*Labor**ln(*Other inputs*)	-0.0527***	0.0189
ln*Water**ln(*Other inputs*)	-0.0052	0.0073
σ_u^2	0.0329***	0.0082
σ_v^2	0.0406***	0.0035
Log likelihood	-133.38	

Note: *p<.10, **p<.05, ***p<.01.

The output elasticities of wheat yield with respect to each input are reported in Table 4.4. The results are in line with Tang et al. (2013a). The highest elasticity is for *Other inputs* (0.46), followed by *Land* (0.44) and *Labor* (0.1132). The elasticity of *Water* is 0.0812 indicating that a 1% increase in irrigation water leads to only a 0.0812% increase of output. The sum of elasticities with respect to the four inputs equals 1.09, indicating a (slightly) increasing return to scale.

Table 4.4 Output elasticities

Input	*Land*	*Labor*	*Water*	*Other*	Sum
Elasticity	0.4444	0.1132	0.0812	0.4561	1.0949

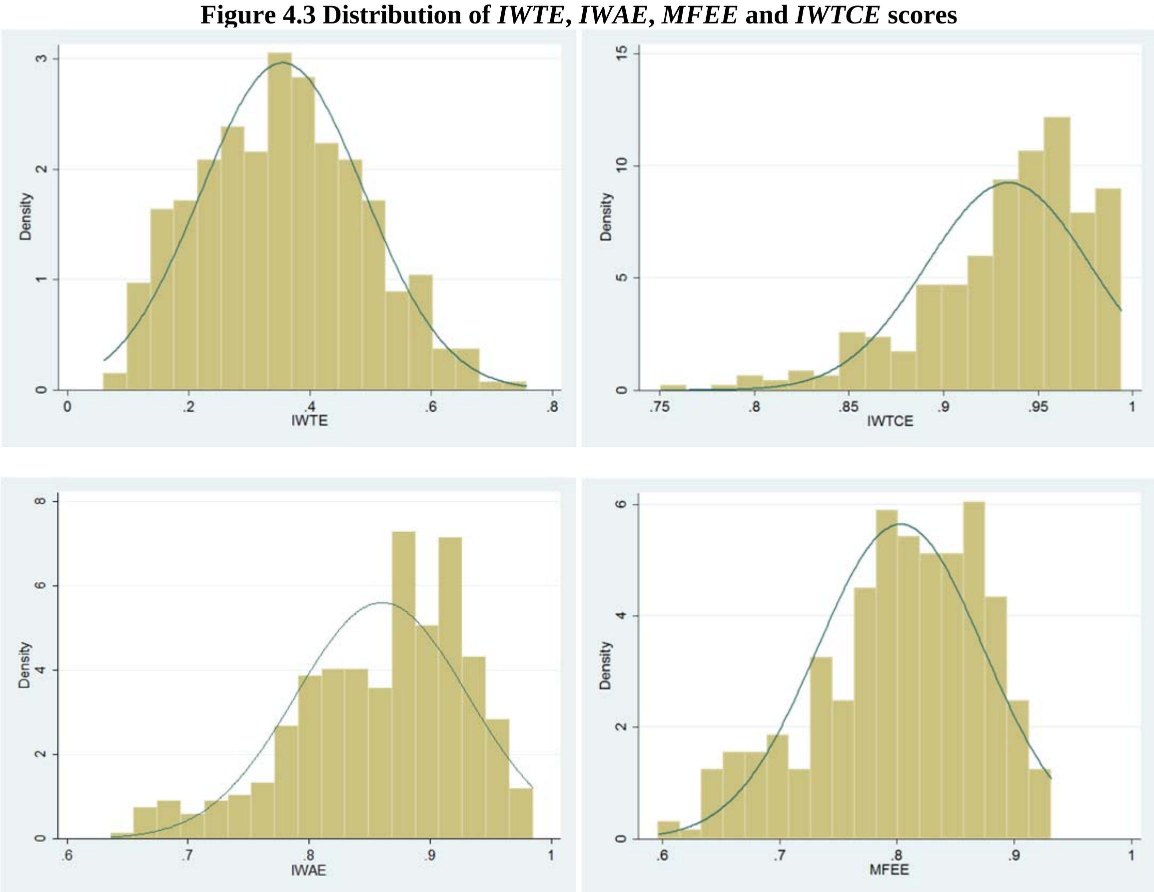
Source: The author.

The estimated distributions of the *IWTE*, *IWTCE*, *IWAE* and *MFEE* scores are shown in Figure 4.5. The *IWTE*, *IWAE* and *MFEE* distributions are close to normal while the *IWTCE* distribution is skewed to the right limit of 1. The mean value of *IWTE* is 0.35, indicating that given current technology and keeping other inputs constant, the same output can be produced by using 65% less water. This means that a large proportion of irrigation water is wasted. However, it also indicates a substantial saving potential. *IWTCE* has a mean value of 0.93, which means that the inefficient use of water leads to a 7% increase of total cost.

IWAE measures farmers' ability to minimize cost using the optimal level of inputs. Its mean value is 0.86, indicating that not allocating the inputs at cost-minimizing proportions has led to a total cost increase by 14%. *MFEE*, which is the product of *IWTCE* and *IWAE*, has a mean value of 0.80. It shows that the total cost can be feasibly decreased by 20% while keeping output at the observed level.

On the basis of the above, we can draw the following conclusion. Since its cost accounts for only 9.85% of total cost, the price of irrigation water can be more than doubled (i.e. increased by the factor 2.03 to give the feasible cost decrease of 20%), without hampering farmers' income, if they improve efficiency by using irrigation water technically efficiently, and optimally allocating their inputs.

Figure 4.3 Distribution of *IWTE*, *IWAE*, *MFEE* and *IWTCE* scores



4.4.3 SEM

Before going into detail, we observe that we assigned a measurement scale to the latent variable *Perception* (which is a prerequisite for identification) by fixing its variance (at 1). Furthermore, the coefficients presented below are standardized (obtained by computing the z-scores and running the analysis using the z-scores, rather than the original scores of the variables). Standardized coefficients allow direct comparisons of the effects of the explanatory variables because their relative movements are the same. For variables measured in other units than z-scores, this does not hold. (As is well-known, if we change the scale of a variable, say, from ounces to pounds, the coefficient will change accordingly (in the example, the new coefficient will be the corresponding old coefficient divided by 16. See Wooldridge (2000) for further details.) Finally, note that we estimated the model by means of LISREL 8.8 (Jöreskog and Sörbom, 2001). Because of the presence of ordinal variables, we analyzed a polychoric correlation matrix.

The measures of model fit are presented in Table 4.5. The p-values corresponding to the χ^2 statistics indicate the probability of obtaining a sample as the one at hand, if the hypothesized conceptual model is true. Since the p-value corresponding to the χ^2 statistic tends to be depressed, if the distribution of the observed variables deviates from normality (Bollen, 1989), we may take the p-value obtained here to indicate a good fit. The other statistics in Table 4.6 also indicate good overall fit, since they meet their critical values by wide margins.

Table 4.5 Goodness of fit statistics

Statistics	χ^2	NFI	GFI	AGFI	RMSEA
Values	34.54(df=28, p=0.1835)	0.926	0.985	0.951	0.026

Note: The cut-off values for NFI, GFI, AGFI and RMSEA indicating a good fit are 0.90, 0.95, 0.90 and 0.06, respectively (Hooper et al., 2008). Put differently, the higher the NFI, GFI and AGFI values and the smaller the RMSEA, the better the fit.

We now discuss the estimated measurement model in Table 4.6. The standardized coefficients of the indicators of *Perception* are all significant. Moreover, the reliabilities (R^2) are above the recommended level of 0.20 (Jöreskog and Sörbom, 2001), indicating that the three indicators measure *Perception* well. The most reliable indicator is *Percep1*, followed by *Percep2*, and *Percep3*. Apparently, perceptions of the present and past situation, as measured by the first 2 indicators, is more reliable than perception of the future, as expected.

Table 4.6 The measurement model (standardized coefficients)

Variables	Indicators	Coefficient	t-value	R^2
	Percep1	0.834	6.682	0.66
Perception	*Percep2*	0.529	6.174	0.29
	Percep3	0.473	5.826	0.23

Source: The author.

The structural models are presented in Table 4.7. We first discuss the efficiency sub-models, next the perception sub-model. In line with the conceptual model, *Perception* impacts positively and significantly on *IWAE*. The impact on *IWTE* is positive, though insignificant at conventional levels. These results indicate that farmers with better perception of water scarcity use irrigation water more efficiently. The impact of *Age* is not significant in the *IWTE* and *IWAE* equations although its sign is as expected. This outcome is probably due to the fact that irrigation requires few skills and little farming experience. *Time* has a negative and significant impact on *IWTE* while its negative impact on *IWAE* is insignificant. *Fragmentation* on the other hand reduces *IWAE* at 10% significance level and *IWTE* at 11% significance level. The positive and significant coefficients of *Infrastructure* in the *IWTE* and *IWAE* equations indicate that repaired canals reduce leakage of irrigation water and improve accessibility. *Income* positively and significantly impacts on *IWTE,* and on *IWAE*.

Table 4.7 The structural model (standardized coefficients)

Variables	*Perception*	*IWTE*	*IWAE*
IWTE	-0.361(0.202)*	----	----
IWAE	-0.568(0.186)***	----	----
Perception	----	0.326(0.246)	0.770(0.360)**
Age	----	0.071(0.064)	0.093(0.075)
Education	0.036(0.067)	----	----
Time	----	-0.135(0.065)**	-0.104(0.076)
Fragmentation	----	-0.108(0.066)	-0.143(0.078)*
Infrastructure	----	0.172(0.072)**	0.205(0.086)**
Income	-0.095 (0.074)	0.145(0.071)**	0.162(0.084)*
Waterprice	0.179(0.068)***	----	----
Precipitation	-0.300(0.070)***	----	----
R^2	0.496	0.128	0.385

Note: Standard errors are in parentheses.
$^{*}p<.10$, $^{**}p<.05$, $^{***}p<.01$.

We now turn to the *Perception* sub-model. The impacts of *IWAE* and *IWTE* are negative and significant indicating that efficient farmers perceive water scarcity less as a problem. As postulated in the conceptual model, a likely explanation is that efficient farmers are of the opinion that water scarcity can be reduced by improving efficiency. The impact of *Education* is positive, though insignificant. Apparently, perception of water scarcity does not require much education. The impact of *Income* is negative, though insignificant. The outcome indicates that access to information as facilitated by *Income*, does not play much of a role. *Water price* has a positive and significant impact, indicating that *Water price* is an important signaling mechanism. Finally, *Precipitation* impacts *Perception* negatively and significantly, as assumed.

The non-zero estimates in the Ψ matrix are shown in Table 4.8. Element ψ_{21} is positive and significant, indicating that the error terms in the *IWTE* and *IWAE* equation are correlated, thus confirming the use of the SUR structure. Note that ψ_{33} is 1, because the variance of the latent variable *Perception* is fixed at 1 to fix its measurement scale.

Table 4.8 Estimated Ψ matrix

Element	Coefficient	t-value	Element	Coefficient	t-value
ψ_{11}	1.182***	4.688	ψ_{22}	1.499***	3.736
ψ_{21}	0.636***	2.459	ψ_{33}	1.000	----

Note: Standard errors in parenthesis.
*p<.10, **p<.05, ***p<.01.

Table 4.9 shows the total effects of all variables on *Perception*, *IWTE* and *IWAE*. The total effect is the sum of the direct effect (the coefficients in Table 4.6) and the indirect effect which is the effect of a variable on an endogenous variable via intervening endogenous variables. Note that an endogenous variable can have a total effect on itself due to reciprocal or circular paths. The system is stable and the total effects are finite if the stability index is less than 1. For the present case study it is 0.847.

Table 4.9 Estimated total effects (standardized coefficients)

Variables	*Perception*	*IWTE*	*IWAE*
IWTE	-0.232(0.141)*	-0.076(0.087)	-0.179(0.093)*
IWAE	-0.365(0.078)***	-0.119(0.074)	-0.281(0.157)*
Perception	-0.357(0.150)**	0.210(0.133)	0.495(0.123)***
Age	-0.051(0.037)	0.054(0.055)	0.055(0.050)
Education	0.023(0.043)	0.008(0.016)	0.018(0.033)
Income	-0.154(0.064)**	0.095(0.053)*	0.043(0.053)
Time	0.069(0.039)*	-0.112(0.056)**	-0.051(0.051)
Water price	0.115(0.054)**	0.037(0.027)	0.089(0.038)**
Infrastructure	-0.115(0.040)***	0.134(0.052)**	0.116(0.047)**
Fragmentation	0.077(0.037)**	-0.082(0.052)	-0.083(0.046)*
Precipitation	-0.193(0.070)*	-0.063(0.042)	-0.149(0.045)***

Note: Standard errors in parenthesis.
*p<.10, **p<.05, ***p<.01.

The variable with the largest total effect on *Perception* is *IWAE* with a negative effect of 0.365, followed by *Perception* and *IWTE,* with negative effects of 0.357 and 0.232, respectively. *Precipitation*, *Income* and *Infrastructure* also have significant, negative effects (0.193, 0.154 and 0.115, respectively). *Water price*, *Fragmentation* and *Time* have significant, positive effects of 0.115, 0.077 and 0.069, respectively. *Age* and *Education* have insignificant total effects on *Perception*.

Infrastructure and *Income* have positive and significant total effects on *IWTE* of 0.134 and 0.095, respectively. *Time* has a significant negative total effect (0.112). The total effects of other variables on *IWTE* are insignificant.

The variable with the largest, significant positive total effect on *IWAE* is *Perception* (0.495). The other variables with significant positive total effects are *Infrastructure*

(0.116) and *Water price* (0.089). *IWAE*, *IWTE*, *Precipitation* and *Fragmentation* have significant negative total effects on *IWAE* of 0.281, 0.179, 0.149 and 0.083, respectively.

4.5 Discussions and policy recommendations

Due to reduced precipitation, accelerating industrialization and urbanization, improvement of efficiency of irrigation water use is crucial for sustainable development and food security in the Guanzhong Plain (and other arid regions in China), because irrigation consumes about 60% of total water resources. By simultaneous estimation of a translog production function and its associated cost-minimizing conditions, we obtained farmers' irrigation water technical, allocative and economic efficiency, based on data collected from 347 wheat farmers. In a second stage analysis we examined the determinants of irrigation water technical and allocative efficiencies by means of a structural equation model. The main results are as follows.

Overall economic efficiency is estimated at 0.80 on average, indicating a substantial (cost) saving potential via optimization of water usage and management. Irrigation water technical efficiency is low at 0.35 which indicates a potential for substantial water saving. Improving technical efficiency of irrigation water use could lead to 7% total costs saving. In addition, improvement of allocative efficiency could lead to a further total cost saving of 14%. This result implies that under current technology, farmers' income losses due to higher water prices can be offset by increasing water use efficiency.

The analysis of the determinants of efficiency reveals that perception has the largest, positive impact on efficiency. Hence, extension is a major policy handle. Tang et al. (2013b) show that extension should be aimed at social networks. Another reason to focus on extension is that perception sets in motion an iterative process in which perception improves efficiency, but also vice versa: efficient farmers have a more optimistic view of combating water scarcity via improved efficiency.

Another instrument to improve perception, and thus indirectly efficiency, is water price in that it signals water scarcity. Furthermore, higher water prices reduce the differences in marginal returns of water use in agriculture, industry and in the residential sector.

The results of the paper furthermore confirm the importance of irrigation infrastructure. Particularly, half of the irrigation canals are in a poor state which leads to poor accessibility and loss of water when irrigating. Therefore, repair projects should be stimulated. Note that such projects would not only improve farmer technical efficiency, but also canal-wide efficiency. We also found evidence that land fragmentation decreases efficiency. As a first step to resolve this problem, integrated management of fields could be introduced to facilitate the introduction of improved irrigation technology such as tubes which would reduce seepage during transportation, particularly to distant plots. It would also reduce labor input into irrigation and thus reduce low efficiency due to part time farming.

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Chapter 5

Adoption of irrigation water-saving techniques in the Guanzhong Plain, China[38]

Abstract: Northern China has been facing rapidly increasing water shortage problems which will have substantial impacts on food security, economic development and the environment in the region, China, and even internationally via shocks in international grain markets. A major reason for water shortage in Northern China is inefficient use of irrigation water. This paper analyses adoption of irrigation water saving techniques, based on a cross-sectional data set of 360 farmers in the Guanzhong Plain, China. Approximately 83% of the farmers use at least one household water-saving technique. However, the traditional, inefficient techniques such as border and furrow irrigation are still prevalent. The use of advanced, efficient techniques is rare. We develop and estimate an adoption model consisting of two stages: awareness of water scarcity and intensity of adoption. We find that production risk, risk-aversion, awareness of water scarcity and financial status positively affect the intensity of adoption while age has a negative impact. From the results it follows that adoption can be stimulated directly via financial support and indirectly via extension aimed at enhancing awareness of water scarcity.

JEL classification: D81 Q12 Q15 Q55

Keywords: Water-saving technique, Adoption, Social network, Production risk, Risk attitude, Extension, China

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5.1 Introduction

China's economy has been growing at an average rate of 10% a year since the economic reforms in 1978. However, this unprecedented growth has been achieved at the cost of its environment and has generated immense pressure on China's natural resources, especially water (Moore, 2013). Li (2006) observes that of China's 662 cities, 300 have been suffering from water shortage and 110 from severe water shortage. 27,000 rivers, more than 50% of China's total in the 1950s, has disappeared (*The Economist*, Oct 12th 2013). The share of crop areas hit by droughts has increased by 16%, causing an annual loss of 27 million tons of yield (Chen et al., 2014). Former prime minister Wen Jiabao, summarized the problem by saying that water shortage is threatening "*the very survival of the Chinese nation*" (*The Economist*, Oct 12th 2013).

There are multiple reasons that have caused water shortage. First, China is endowed with limited water resources. Average annual water availability was 2100 m^3 per capita in 2010, close to the threshold of 'water stress' of 2000 m^3 per capita[39]. Besides, water resources are unevenly distributed, both temporally and spatially. Water is abundant in the south but scare in the north. The North China Plain, known as the 3H (Huang Huai, and Haihe) river basin, contains 40% of China's arable land and produces 50% of its grain, but is endowed with only 8% of the national water resources. Due to a continental monsoon climate, 60-70% of China's annual precipitation is concentrated in the June-September period. This percentage is close to 80% in northern regions. The temporal variation adds difficulties to utilize the water (Cheng et al., 2009).

Secondly, demand for water has been growing rapidly from 443.7 km^3 in 1980 to 614.2 km^3 in 2012. What is more, it is expected to continue to grow (Jiang, 2009). The main drivers of the rapidly growing demand for water have been population and income growth, industrialization and urbanization. The current population of 1.36 billion is expected to peak at 1.6 billion in 2030 with a per capita income of $16,000 (Chen, 2007; World Bank, 2013). The income increase has led to a change in the food consumption pattern from grain products towards meat. The production of 1kg of pork requires 3.5kg of grain and production of 1kg of grain requires 800kg of water (Giordano, 2007). Meat consumption increased from 12.7kg in 1980 to 20.7 kg in 2012 (NBSC, 2013).

[39] Following UNDP, UNEP, World Bank and the World Resources Institute, a region is "water stress" if annual water availability per capita is between 1,000 and 2,000 m^3/person, and "water scarcity" if the figure is below 1,000 m^3/person (Shalizi 2006).

The surging demand for water has also been pushed up by rapid urbanization and industrialization. Urban resident consumed 72.3 m^3 per person per year in 2010, which is more than twice the amount consumed by rural resident (29.9 m^3 per person per year) (MWR, 2011). The level of urbanization is expected to rise to 60 percent in 2030, which will put further pressure on water resources. The demand for water from industry has increased from 45.7 km^3 in 1980 to 113.9 km^3 in 2000 and to 142.4 km^3 in 2012.

Thirdly, water availability has decreased due to water pollution and climate change. A volume of 685 billion tons of wastewater was generated in 2012 (NBSC, 2013), of which 80% was discharged untreated into rivers, lakes and the sea (Bao and Fang, 2012). Approximately 40% of China's rivers is severally polluted (water quality below Class IV) and is unfit for human contact (MWR, 2012). This is even worse in the 3H river basins where two thirds of the river water is unfit for human contact. China's lakes are also severely polluted. MWR (2012) reports that 70% of the monitored major lakes suffer from eutrophication.

Fourthly, a significant decrease in annual precipitation has been observed in most of northern China while there is an increase in southern China, leading to more frequent droughts in the North and floods in the South (Wang et al., 2012). Besides, an increase in frequency and intensity of extreme climate events has been observed (Piao et al., 2010).

The Chinese government is aware of and has responded to the water shortage problem in northern China. However, the strategies focus on augmenting water supply rather than controlling water demand (World Bank, 2009). Among the water resource management strategies, the South-North Water Transfer Project (SNWTP), launched in 2002, is perhaps the best known. Upon completion by 2050, the project is expected to transfer annually 45 km^3 water from central and southwest China to meet 20% of current water demand in the 3H basin (Berkoff, 2003). Although the project will bring about $3 billion economic return annually, the rationality is still debated (Berkoff, 2003). The total investment will reach $62 billion, not to mention the social cost and environmental consequences. At least 300,000 residents along the central route will be resettled (Freeman, 2011). Zhang (2009) summarizes the various environmental consequences of the inter-basin water transfer: water quality degradation along the canal due to untreated industrial wastewater discharge, salinization in the receiving areas, invasion of alien species and river ecosystem changes in the water supply areas. If all these costs are also counted, the cost per m^3 of water from the SNWTP is estimated to be approximately 20 yuan (3 US dollars), which is more than four times the cost of seawater desalination (5 yuan) (Shi and Feng, 2011).

The North, which accounts for approximately 64% of its arable land, is China's main food production area (Khan et al., 2009). Annual water availability of 750 m^3 per capita is far below the threshold of 1000 m^3 indicating 'water scarcity'. To supplement limited rainfall, irrigation is widely used to maintain food production at its current level. Approximately 50% of its arable land is irrigated to produce 75% of the North's agricultural output (Tang et al., 2013a). In recent years the risk of droughts in northwestern China has been worsening because of climate change (Piao et al., 2010) which has further raised potential vulnerability of agricultural production. Meanwhile, groundwater extraction has led to a decline of the groundwater table, making underground water supply less reliable (Wang et al., 2007) and raising uncertainty of future water supply even further.

Irrigation consumes 70% of total water withdrawal in the Northwest (MWR, 2011). However, efficiency is very low (Tang et al. 2013a). Therefore, increasing irrigation water use efficiency is a way to reduce water shortage problems, particularly in the short and medium term. A major instrument to achieve this objective is adoption of efficient irrigation techniques.[40]

Lohmar et al. (2003) observes that the adoption rate of efficient water saving techniques in China has remained low, although the Chinese government has strongly encouraged irrigation water saving. Among the three types used, traditional techniques like border and furrow irrigation, are still prevalent, while modern household-based and community-based techniques, like drip irrigation and underground pipelines, are rare (Blanke et al., 2007).

The conventional factors supposed to affect adoption of agricultural techniques include farm and farmer characteristics, availability of credit, information and labor availability (see Feder et al. (1985) for a review). These factors have also been analyzed in relation to the adoption of irrigation techniques (Zhou et al., 2008; Abdulai et al. 2011; among others). In addition, production risk has been found to be an important determinant of adoption of agricultural techniques in general (Feder et al., 1985; Foster and Rosenzweig, 2010; Liu, 2013; among others). However, despite the evidence, production risk is

[40] For other solutions, e.g. irrigation management reform, see Tang et al. (2013a).

frequently ignored in agricultural adoption studies in developing countries like China, because of measurement problems (Liu and Huang, 2013; Just et al., 2010).

The need to consider production risk in adoption studies of agricultural techniques - including irrigation techniques - relating to northern China has increased because precipitation has begun to vary more and more across years because of climate change. Consequently, farmers are facing more and larger unexpected hazards of extreme weather (e.g. extremely low precipitation) which has increased production risk. Hence, a farmer may choose to adopt water-saving techniques to reduce weather-related risk. Meanwhile, attitude towards risk also plays a role in adoption behavior (De Pinto et al., 2013). A risk-averse farmer may hedge against weather risk by adopting water-saving techniques while the opposite is likely to hold for a risk-loving farmer.

The main objective of this paper is to analyze the adoption of irrigation techniques in the Guanzhong Plain, Shaanxi Province, China. In addition to the conventional determinants, notably demographic and socio-economic factors and farm characteristics, we will also consider production risk and farmer attitudes towards risk.

The paper is organized as follows. Section 5.2 presents the conceptual adoption model and Section 5.3 discusses estimation of production risk and risk preference. Section 5.4 describes data collection and presents the empirical results. Section 5.5 concludes and presents policy recommendations.

5.2 Conceptual model

As a first step, we present a brief overview of irrigation techniques applied in the study area. For this purpose, we follow Wang et al. (2002) who points out that irrigation consists of the following three stages: (i) delivering water from reservoirs or groundwater pumping stations to the fields; (ii) transferring water from fields to crop root; and (iii) uptake by the crop.[41] Each stage may incur water losses which can be reduced by stage-specific methods and techniques.

For the delivering to the field stage, the following techniques are in use in the survey area. (i) *Earthen-lined canals*. The walls of these canals are made of earth and thus are highly permeable which leads to seepage, up to as much as 50% of total transport (Wang

[41] We do not discuss other water saving techniques, such as rainwater collection and intermittent irrigation, which are not applied in the survey area.

et al., 2002). (ii) *Cement-lined canals*. This kind of canals is less permeable than earthen-lined canals which reduces seepage. Moreover, cement-lined canals have smoother surfaces than earthen-lined canals resulting in faster flow velocity which also reduces seepage and evaporation. (iii) *Pipelines*. This is a network of underground or surface pipes that are used to transfer irrigation water from the water source to the fields. The pipelines are usually connected to a station that pumps water from an underground source or from a major canal.

For the second stage, the following techniques are in use in the study area. (i) *Flood irrigation.* This technique lets the water flow along the fields. There are no barriers such as furrows or ridges that control the flow. It is popularly called a '*water-waste irrigation technique*', because a large proportion of the water is wasted due to seepage and evaporation. (ii) *Border irrigation.* This technique divides a plot into several strips by soil ridges (borders) (Wang et al., 2002). Water is released into the area between the borders which guide water flows down the field. Border irrigation is more efficient than flood irrigation in that water flows to the end of the field in a shorter period of time and thus reduces seepage and evaporation. (iii) *Furrow irrigation.* This technique dugs small, parallel ditches (furrows) into a plot through which the irrigation water flows to the crop beds. It is suitable for row crops that are usually grown on the ridges between the furrows. Water is infiltrated to the crop roots without wetting the entire surface. It is thus more efficient than flood irrigation. (iv) *Sprinkler* and *drip irrigation.* These techniques pump water to the fields through a system of small pipes. Water is dripped or sprayed by emitters installed on the pipes.

At stage three, water absorption can be enhanced by adopting drought-resistant varieties or by using agronomy measures such as mulching and fertigation. Under (i) *mulching*, straw or plastic sheeting is placed over the soil surface to reduce evaporation and retain moisture. In the study area, wheat straw is left in the fields and used to cover corn which is grown after the wheat harvest. Plastic sheeting is commonly used in cotton, corn and vegetables cultivation. (ii) Use of *drought-resistant varieties* can significantly reduce vulnerability to droughts. These varieties have the ability to grow and produce satisfactory yields under drought conditions. (iii) *Fertigation* is the integration of fertilization and irrigation. Soluble fertilizers and other chemicals are directly applied to irrigation water surrounding the root zone of plants, resulting in a more efficient use of both water and fertilizers. Specifically, water enriched with fertilizers increases the soil structure which improves crop root growth, drought resistance and increases water storage capacity (Wang et al., 2002).

We now turn to the structure of the adoption model. A vast literature has focused on adoption of agricultural techniques. The models applied fall into two categories: static and dynamic (Marra et al., 2003). The former kind uses cross-sectional data and identifies the characteristics of the adopters against the non-adopters. Studies of this type include amongst others Green et al. (1996); Abdulai et al. (2005, 2011) and Zhou et al. (2008). The dynamic approach analyzes adoption of a specific technique over time, usually by means of a diffusion curve, estimated on the basis of panel data (Dinar and Yaron 1992; Carey and Zilberman 2002; among others). Due to data collection constraints, the static model is more widely used than the dynamic model. However, by its very nature, the static approach does not allow modeling of the dynamics of the adoption decision (Doss, 2006).

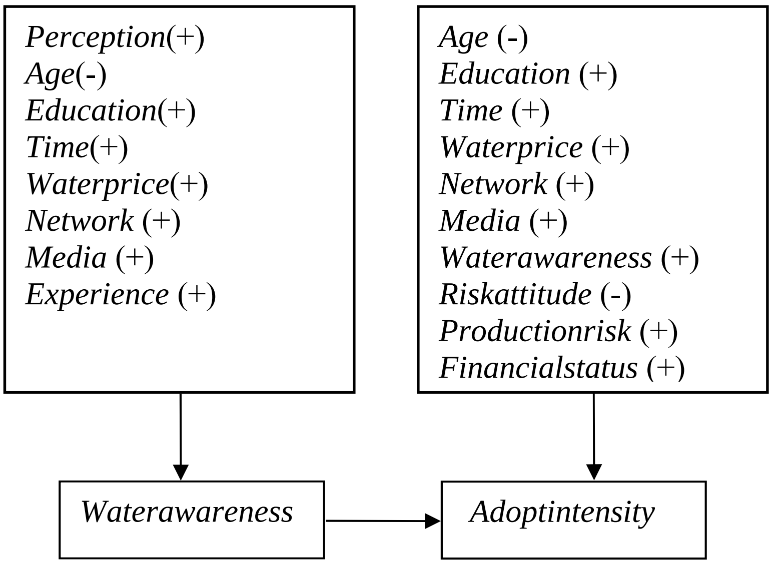
The present study is also based on cross-sectional data. However, we (partly) overcome its disadvantage by taking adoption as a sequential, multi-stage process, as suggested by among others Ervin and Ervin (1982), Semgalawe and Folmer (2000), Dimara and Skuras (2003), Bewket (2007) and De Graaff et al. (2010). The model suggested in these literatures is a three-stage model consisting of the following stages: (1) perception of the problem, (2) the decision to adopt or not, and (3) intensity of adoption. The decision to adopt or not can be conveniently captured by the intensity of adoption in that no adoption can be taken as intensity equal to zero. Hence, we propose the following two-stage model: (1) awareness of water scarcity (*Waterawareness*), and (2) intensity or extent of adoption (*Adoptintensity*). We present the conceptual adoption model in Figure 5.1.[42]

We now present definitions and measurements of the core variables in Figure 5.1. We first discuss the *Waterawareness* model. The discussion follows Tang et al. (2013b) to which we refer for details. Perception of water scarcity, denoted *Perception*, is defined as the recognition of the state of water availability as problematic. It is a latent variable measured by the following indicators: *Percep1* (knowledge of current water availability status), *Percep2* (knowledge of change of water availability), *Percep3* (knowledge of change of water quality) and *Percep4* (expectation of future water scarcity). Each

[42] For a description of the survey, see section 5.3.

indicator is measured on a 5-point scale ranging from “strongly disagree” to “strongly agree”. *Waterawareness* is defined as a farmer’s attention to, and concern about, water scarcity and its negative impacts on production. It is measured in this paper by the responses to the following three statements: (i) availability of irrigation water is hindering agriculture production; (ii) I always worry about irrigation water shortage; (iii) saving irrigation water is important. For each of the statements there is a 5-point scale, ranging from “strongly disagree” to “strongly agree”. Tang et al. (2013b) shows that *Waterawareness* is highly dependent on perception of water scarcity (*Perception*) and vice versa. Therefore, we apply the same structural equation model (SEM) as in Tang et al. (2013b) to obtain predictions of *Waterawareness* as explanatory variable of the adoption model.

Figure 5.1 The conceptual adoption model



Note: The above system is a recursive system which implies that each equation can be estimated separately.

We measure *Adoptintensity* on the basis of the number of household-based measures adopted (Paxton et al., 2011), as well as their efficiency and complexity of application. The irrigation techniques are classified into three categories according to their complexity from low to high: traditional (furrow and border irrigation), intermediate (mulching and surface pipe) and advanced (fertigation and drought resistant varieties). The *Adoptintensity* variable takes the value 0 in the case of non-adopters (flood irrigation is considered non-adoption), 1 if a farmer has adopted either of the traditional techniques, 2 if both, 3 either of the intermediate techniques, 4 both, 5 either of the advanced techniques, and 6 both.

The following farmer and farm characteristics are exogenous variables in Figure 5.1: *Age*, *Education*, *Waterprice*, *Riskattitude*, *Productionrisk*, *Time*, *Financialstatus*, *Network* and *Media*. Measurement of *Age* is straightforward. *Education* is measured as years of schooling. *Time* is taken as the response to the following question: "How much of your working time do you spend on farming?" It is measured on a 5-point scale: 1=0-19%, 2=20-39%, 3=40-59%, 4=60-79%, 5=80-100%. *Waterprice* is the price a farmer pays for irrigation water. *Riskattitude* and *Productionrisk* are farmers' attitudes toward risk and production risk, respectively. The measurement of both variables is described in the next section. *Financialstatus* is the response to the question "I have enough money to invest in water-saving techniques". It is measured on a 5-point scale ranging from "strongly disagree" to "strongly agree". *Network* indicates a farmer's connection to his or her peers. It is measured by the following four indicators: (i) I often discuss water scarcity issues with other villagers (*Network1*); (ii) I am a member of a water users' association (WUA) (*Network2*); (iii) I have relatives or neighbors who are using water saving technologies (*Network3*); (iv) I have relationships with the local government and irrigation managers (*Network4*). *Network1* is measured on a 5-point scale ranging from "strongly disagree" to "strongly agree". *Network 2-4* are dichotomous variables taking the value 1 if "Yes", and 0 if "No". *Network* is the sum of *Network1-5*. *Media* represents a farmer's access to media which is measured by the following four questions: (i) How many times a week do you watch TV or do you listen to the radio? (ii) How many times a week do you read newspapers or books? (iii) How many times a week do you surf the internet? (iv) How many times a year do you see slogans or propaganda about irrigation water saving? The four questions are measured on 5-points scales ranging from "never" to "more than 7 times a week". The scores of the four questions are summed to form a respondent's total score on *Media*. Drought experience, denoted by *Experience*, is measured by inviting the respondents to answer the question: "In the past, it was easy to get water when I irrigated my land." on a scale ranging from 1 (strongly disagree) to 5 (strongly agree). The impacts of the exogenous variables on each of the two adoption stages are given in Figure 5.1 where + and – indicate the expected sign.

5.3 Definition and estimation of production risk and the risk preference function

Production and output price uncertainty are two of the main sources of production risk (Kumbhakar, 2002). In this paper, we do not consider output price uncertainty because the price for grain (the commodity considered in the paper) in China is stable and farmers are generally price takers. Hence, we only consider production risk.

To account for production risk, production function (1), introduced by Just and Pope (1978) and developed by Kumbhakar (2002), is widely used:

$$Y = f(X) + g(X)\varepsilon, \tag{1}$$

where Y is output divided by per mu of land, X a vector of inputs which includes labor, water and other inputs per mu and ε the error term[43]. Following Kumbhakar and Tsionas (2010), we assume that $E(\varepsilon|X) = 0$ and $E(\varepsilon^2|X) = 1$. The production function is composed of two components: (i) $f(X)$, the mean production function, irrespective of production risk; and (ii) $g(X)$, the output risk (variance) function which represents the effect of each input on production risk.

We assume that farmers maximize expected utility of profit under production risk. That is, for the mean production function and risk function, the farmer faces the following problem (Kumbhakar and Tsionas, 2010):

$$\text{Max E}(\text{U}(\pi)) = \text{Max E}\left[\text{U}\left(p_y f(X) + p_y g(X)\varepsilon - \textstyle\sum_{j=1}^{J} p_j x_j\right)\right] \tag{2}$$

where U(.) is the Von Neumann-Morgenstern (1947) expected utility function which is assumed continuous and differentiable, π is profit, p_y the price of yield and p_j the price of input j. The first-order conditions (FOC) of utility maximization with respect to the three inputs are:

$$\text{E}\left(\text{U}'(\pi)\right)\left\{p_y f_j(X) + p_y g_j(X)\varepsilon - p_j\right\} = 0 \quad \text{j=labor, water, other inputs} \tag{3}$$

where $\text{U}'(\pi)$ is the partial derivative of the profit function with respect to input j, $f_j(X)$ and $g_j(X)$are the partial derivatives of $f(X)$ and $g(X)$ with respect to j, respectively.

According to Kumbhakar and Tveteras (2003), equation (3) can be rearranged as follows:

$$\frac{p_j}{p_y} = f_j(X) + g_j(X)\theta_j(p_j, p_y, X) \qquad \text{j=labor, water, other inputs} \tag{4}$$

where

[43] Land is not explicitly included, since labor, water and other inputs are per unit of land.

$$\theta(.) = \frac{E(U'(\pi)\varepsilon)}{E(U'(\pi))} \tag{5}$$

is an indicator of a farmer's risk preference. If $\theta(.)$ =0, the left-hand side of (4) is equal to the first term on its right-hand side indicating that the marginal profit of input j equals the price of j. The farmer is considered risk-neutral in this case. If $\theta(.)$ <0, the left hand side of (4) is smaller than the first term on the right hand side, indicating that the farmer is risk-averse since he/she uses less j than a risk-neutral farmer. In a similar vein, a farmer is considered risk-loving if $\theta(.)$ >0 (Kumbhakar and Tsionas, 2010).

We now turn to estimation of the production risk function $g(X)$ and the risk preference function $\theta(p_j, p_y, X)$. Estimation can be parametric or nonparametric. We opt for the nonparametric approach because parametric estimation of the system consisting of these functions together with the production function $f(X)$, frequently leads to convergence and stability of the estimates while the system of first-order conditions is ill-behaved (Kumbhakar and Tsionas, 2009). Therefore, following Kumbhakar and Tsionas (2009, 2010) and Gerard and Hennings (2013), we apply a non-parametric approach. Under this approach, output Y is regressed on X to obtain the predicted $\hat{f}(X)$ and the residual $e = Y - \hat{f}(X)$ using multivariate kernel regression (for details see Kumbhakar and Tsionas, 2010). The variance of output Y, $PR = e^2$, is taken as production risk (PR). Note that a larger value of e^2 indicates a higher production risk. The production risk function is estimated by regressing the absolute value of the residual e on the same set X as in the first step, again by multivariate kernel regression.

The risk preference function is obtained by rearranging (4) to give:

$$\theta_j(p_j, p_y, X) = \frac{\frac{p_j}{p_y} - f_j(X)}{g_j(X)} \quad j\text{=labor, water, other inputs} \tag{6}$$

From (6) it follows that the partial derivatives with respect to X_j, viz. $f_j(X)$ and $g_j(X)$, are needed. They can be obtained from the estimated $f(X)$ and $g(X)$. Since there is a first-order condition for each input (three in this paper), there are three risk preference functions, one for each input. Since we are only interested in the risk preference functions with respect to water, we ignore the other two risk preference functions.

The estimated production risk scores e^2 and risk preference scores for water together with the other explanatory variables are used to estimate the *Waterawareness* and *Adoptionintensity* models, presented in Figure 5.1.

5.4 Data and descriptive statistics

5.4.1 Data collection and sampling

Data, based on a stratified sample of 446 farmers in the Guanzhong Plain, was collected by the first author using face-to-face interviews. The survey took place in October, 2011 when the harvest of the seasonal crop was finished. The Guanzhong Plain is the main area for agricultural production in Shaanxi province. It has well-structured irrigation canal systems which transfer water from rivers and reservoirs to the fields. Irrigation is organized by irrigation districts. Each district has its own water source, canal system, and irrigation management bureau.

The sampling scheme was four-stage stratified random sampling. In the first stage, the nine largest out of 100,000 irrigation districts were selected which cover 80 percent of the total irrigated area. In the second stage, 2 to 12 canals were randomly sampled per irrigation district proportionally to the total number of canals within the district. The canals irrigate one or more villages. At stage three, one upstream and one downstream village were randomly selected per canal. Finally, 5 to 7 farmers were randomly chosen per village, resulting in a sample of 446 farmers.

We only considered the farmers who grow wheat and corn. The reason is that the prices of these crops fluctuate less than those of cash crops such as apple, kiwi and pear. Thus, for the selected crops the production risk only stems from production uncertainty rather than from output prices. We also excluded the non-irrigators, resulting in a sample size of 360 farmers.[44]

The respondents were asked to provide information on crop-specific inputs and outputs for the entire crop season. Since there are no precise devices in the area to gauge the exact volume of water extracted, this information was inferred from the number and durations of irrigation spells, and size of the canal. Most of the farmers were able to report how much water they extracted per hour and the total number of hours. If this was not the case, we used information obtained from other farmers in the village with similar plot sizes and outputs to estimate the volume.

[44] There are 55 non-irrigators. The reasons for non-irrigation are: (1) abundant rainfall (reported by 32 farmers); (2) no irrigation infrastructure available (25); (3) excessively high water price (17); (4) irrigation considered not profitable (5); (5) lack of labor (2).

Table 5.1 presents overall descriptive statistics for the variables included in the analysis. *Output* is measured in Yuan/mu. The three inputs include: (i) *Labor* (measured in man-days/mu); (ii) *Water* (measured in m^3/mu); and (iii) *Other* (the sum of all other inputs including seeds, fertilizers, pesticides, plastic sheeting and machinery, measured in Yuan/mu).

Table 5.1 Overall Descriptive Statistics

Variable	Unit of Measurement	Mean	S.D.	Min	Max
Output	Yuan	8506	7027	405	75800
Land	Mu	10.91	7.40	1	80
Labor	man-days	23.66	31.35	0.6	280.9
Water	m^3	2690	2787	75	23472
Other	Yuan	3412	2933	144	33680
Age	Years	53.10	10.16	26	77
Education	Years	6.65	1.70	0	12
Water price	Yuan/m^3	0.32	0.14	0.02	1.16
Network	----	6.22	1.49	4	10
Media	----	8.96	2.16	4	20
Experience	----	2.71	1.48	1	5
Financialstatus	----	2.15	1.23	1	5
Adoptintensity	----	1.59	1.64	0	6

Notes: (1) Sample size 360; (2) This table partly overlaps with Table 1 in Tang et al. (2014); (3) Risk and risk attitude scores are presented in Section 5.5; (4) Source: first author's survey.

Adoption of the household-based irrigation technologies is displayed in Table 5.2.[45] The vast majority (82%) of the farmers still use the traditional techniques furrow and border irrigation. Even more so, flood irrigation is still common and applied by 17.78%. Finally, only 5.56% of the farmers use drought-resistant varieties and approximately 10% apply mulching and fertigation.

Table 5.3 shows further details on *Adoptintensity*. The techniques are ranked on the basis of efficiency and complexity of application while per technique the numbers and proportions of adopters are presented. 62 (17.22%) farmers use flood irrigation which is defined non-adoption (see section 5.2). Among the 217 farmers who have adopted either of the traditional techniques, 211 (97%) have chosen furrow irrigation. Only 2 farmers adopted both of the two traditional techniques. A number of 23 (6.39%) farmers used intermediate techniques but did not use advanced techniques, of which 14 used surface pipe and 9 for mulching. The next category (both intermediate techniques adopted while

[45] The water-saving techniques can be classified into two categories, namely household-based and community-based techniques. The former type includes flood, border, furrow, drought-resistant variety, mulching and fertigation while earthern-lined canal, cement-lined canal, underground pipeline, drip, sprinkler fall into the latter. We only focus on the household-based irrigation techniques because their adoption is decided by individual farmers, rather than by a group of farmers. The adoption of community-based techniques is not discussed because adoption of which is a collective (group) behavior.

neither advanced techniques adopted) has 5 (1.39%) farmers. Next, approximately 12% of farmers have adopted either of the advanced techniques. Finally, 8 farmers are assigned the highest points for adopting both fertigation and drought-resistant varieties.

Table 5.2 Descriptive statistics: Adoption of WSTs

Stage of the irrigation process	Irrigation technology	Adoption	(%)
Stage I	Earthern-lined canal	----	----
	Cement-lined canal	----	----
	Underground pipeline	----	----
	Surface pipe	17	4.72%
Stage II	Flood	64	17.78%
	Border	13	3.61%
	Furrow	283	78.61%
	Drip	----	----
	Sprinkler	----	----
Stage III	Drought-resistant variety	22	5.56%
	Mulching	40	10.28%
	Fertigation	40	10.83%

Notes: (1) sample size 360; (2) adoption relates to household techniques only; (3) Source: first author's survey.

Table 5.3 Descriptive statistics: *Adoptintensity*

Adoptintensity	Border	Furrow	Surface pipe	Mulching	Fertigation	Drought-resistant variety	Number of farmers
0	0	0	0	0	0	0	62(17.22%)
1	6	211	0	0	0	0	217(60.28%)
2	2	2	0	0	0	0	2(0.56%)
3	0	0	14	9	0	0	23(6.39%)
4	0	0	5	5	0	0	5(1.39%)
5	0	0	0	0	31	12	43(11.94%)
6	0	0	0	0	8	8	8(2.22%)
Total							360(100%)

Notes: (1) *Adoptintensity* takes the value 0 in the case of non-adopters (flood irrigation is considered non-adoption); 1 if a farmer has adopted either of the traditional techniques; 2 if both; 3 either of the intermediate techniques; 4 both; 5 either of the advanced techniques; and 6 both. (2) We do not consider other water saving techniques, such as rainwater collection and intermittent irrigation, which are not applied in the survey area.

5.5 The estimated models

Nonparametric multivariate kernel regression estimation of the mean production function and the risk function was done by means of the statistical software package R, add-on package "np". To avoid negative marginal products (i.e. violation of the properties of the production technology), we imposed monotonicity constraints (Parmeter, 2013). Based on the estimated $f(X)$ and its partial derivatives, the elasticities of the mean output with respect to each input were obtained.

The absolute values of the residuals were used to estimate the risk function by means of multivariate kernel regression. The absolute residuals and the explanatory variables - which are the same as in the case of the mean production function - were log transformed before estimation (Czekaj and Henningsen, 2013). As in the case of the mean production function, the elasticities were calculated. Table 5.4 shows the estimated elasticities with respect to the inputs *Labor*, *Water* and *Other inputs* of the mean production function and risk function, respectively. The input with the largest output elasticity is *Other inputs* (0.2303), followed by *Water* (0.0734) and *Labor* (0.0527). Regarding the production risk function, Table 5.4 shows that *Water* (-0.1204) decreases output variability (risk). This result indicates that irrigation helps to maintain a high yield and eliminate risk due to extreme weather events such as droughts. Similar results are reported by Groom et al. (2008). *Labor* also reduces production risk while *Other inputs* increase it.

Table 5.4 Elasticities of inputs of the mean production function and risk function

$f(X)$	Mean	S.D.	Min.	Max.
Labor	0.0527	0.0709	0	0.4213
Water	0.0734	0.0613	0.0001	0.5097
Other	0.2303	0.2304	0.0002	1.9019
$g(X)$				
Labor	0.0489	0.1422	-0.4461	0.5428
Water	-0.1044	0.7455	-4.6351	2.0969
Other	0.0658	0.5571	-1.2922	1.7120
Productionrisk	90.20	77.50	0	494.42
Riskattitude	-0.78	13.66	-152.09	53.96

Source: The authors.

Next, we estimate the *Waterawareness* and *Adoptionintensity* models. As mentioned above, the former is estimated by means of a SEM, as in Tang et al. (2013b).[46] The same consists of a measurement model of the latent variables *Awareness* and *Perception* and a two–equation structural model. The measurement model is presented in Table 5.5. It indicates that *Aware1* (availability of irrigation water is hindering agriculture production) and *Aware2* (I always worry about irrigation water shortage) are reliable indicators of *Awareness* while the reliability of *Aware3* (saving irrigation water is important) has substantially lower reliability (R square). All in all, *Awareness* is reasonably well measured. Similar conclusions apply to measurement of *Perception* by way of the indicators *Percep1* (knowledge of current water availability status), *Percep2* (knowledge

[46] We only present the structural and measurement model. Total effects which are not needed to obtain a prediction of Awareness as input into the adoption intensity model, are available upon request from the first author.

of change of water availability), *Percep3* (knowledge of change of water quality) and *Percep4* (expectation of future water scarcity).

Table 5.5 The measurement models (standardized coefficients)

Latent variable	Indicators	Coefficient	S.E.	R^2
Awareness	*Aware1*	0.572	---	0.327
	Aware2	0.593^{***}	0.072	0.352
	Aware3	0.139^{**}	0.060	0.019
Perception	*Percep1*	0.843	---	0.711
	Percep2	0.503^{***}	0.054	0.253
	Percep3	0.285^{***}	0.056	0.081
	Percep4	0.449^{***}	0.055	0.201

Note: *p<.10, **p<.05, ***p<.01.

Table 5.6 presents the structural model. The results are in line with the structural model in Tang et al. (2013b) to which we refer for a discussion of the *Perception* equation. From Table 5.6 we conclude that *Perception*, *Network. Time* and *Age* are the significant determinants of *Waterawareness*. In line with expectations, we find that *Perception* has a substantial positive impact on *Awareness*. *Network* indicates that farmers who are more connected to peers, water users' groups, relatives, neighbors, and local opinion leaders (*Network*), are more aware of water scarcity than those who are poorly connected. Apparently, one's network is an important source of information about water scarcity. We also find that the more time a farmer spends on farming, the larger his/her *Waterawareness. Age* on the other hand has a negative effect. Apparently, older farmers are less aware of water shortage than their younger peers. Finally, *Education* and *Media* have the wrong sign, but they are highly insignificant. Apparently *Education* is not a prerequisite for awareness of water scarcity. Nor does *Media* play much of a role. Based on the SEM model, the prediction of *Waterawareness* for each farmer is obtained as explanatory variable in the adoption model. The descriptive statistics of *Waterawareness* are shown in Table 5.7.

The *Adoptintensity* model is an ordered probit model. It is estimated via a backward stepwise procedure which starts with the initial model (i.e. the conceptual model) and deletes insignificant variables one by one, starting with the one with the highest *p*-value. Variables with *p* values less than 0.10 were retained. The model thus obtained is denoted final model. The initial and final models are reported in Table 5.8.

Table 5.6 Standardized coefficients of the structural *Awareness-Perception* models

Variables	*Awareness*	*Perception*
Perception	0.700(0.088)***	---
Awareness	---	0.099(0.216)
Age	-0.133(0.063)**	---
Edu	-0.052(0.059)	---
Time	0.150(0.065)**	0.047(0.054)
Media	-0.027(0.057)	---
Waterprice	---	0.033(0.039)
Network	0.347(0.068)***	0.040(0.100)
Experience	---	0.752(0.126)***
R^2	0.789	0.702

Notes: (1) Standard errors in parenthesis. *p<.10, **p<.05, ***p<.01; (2) Although the coefficients of *Awareness* and *Waterprice* in the *Perception* equation are insignificant, we retain them in the model to maintain the similarity to the model in Tang et al. (2013b).

Table 5.7 Descriptive Statistics: *Waterawareness*

Variable	Mean	S.D.	Min.	Max.
Waterawareness	2.77	0.63	1.40	4.08

Table 5.8 The *Adoptintensity*[a] model

Variables	Initial model	Final model
Age	-0.0103(0.0061)*	-0.0117(0.0059)**
Education	0.0242(0.0369)	
Time	0.0088(0.0405)	
Waterprice	-0.2500(0.4285)	
Network	0.0367(0.0521)	
Media	0.0223(0.0279)	
Waterawareness	0.1449(0.1097)	0.1911(0.0826)**
Riskattitude	-0.0121(0.0046)***	-0.0127(0.0045)***
Productionrisk	0.0015(0.0008)*	0.0015(0.0008)*
Financialstatus	0.0995(0.0497)**	0.1063(0.0478)**
R^2	0.0311[b]	0.0293[b]
Log likelihood	-408.54	-411.43

Note: [a] Ordered-probit model; [b] McFadden's pseudo R-squared; Standard errors in parenthesis; *p<.10, **p<.05, ***p<.01.

The final model in Table 5.8 shows that the impact of *Waterawareness* is significant and positive indicating that farmers who are more aware of water scarcity, are more likely to adopt more, and more advanced, WSTs than those who are not aware. Moreover, *Productionrisk* has a positive and significant coefficient. This result indicates that farmers who have experienced production risk tend to hedge against those risks by adopting water saving techniques. In a similar vein and in line with this result, *Riskattitude* stimulates adoption of WSTs. A risk-averse farmer adopts more, and more advanced, WSTs than a risk-loving farmer. This is in line with Finger et al. (2011), among others, who found that risk-averse farmers are more likely to use irrigation as an adaptation strategy to climate change than risk-neutral or risk-loving farmers. *Age* has a negative significant coefficient, suggesting that older farmers are less likely to adopt WSTs. Moreover, since adoption implies investment outlays, it is evident that *Financialstatus* has a positive and significant impact. Except for *Waterprice*, the signs of the coefficients of the other variables are in line with expectation, though not significant.

5.6. Conclusions and policy recommendations

China has been facing rapidly increasing water shortage problems in the North which will have substantial impacts on food security, economic development and the environment in the region, China, and even internationally via shocks in international grain markets. A major reason for water shortage in Northern China is inefficient use of irrigation water. This paper investigates adoption of water-saving irrigation techniques, based on a sample of 360 farmers in the Guanzhong Plain. Adoption is modeled as a sequential process consisting of the stages awareness of water scarcity and intensity of adoption. The main conclusions are the following.

First, the adoption rate of water-saving techniques is high. Approximately 80% of the farmers use at least one household-based water-saving technique. However, the traditional irrigation techniques such as furrow irrigation are still prevalent while the adoption rates of advanced techniques such as mulching, drought resistant varieties and pipelines are low.

Secondly, awareness of water scarcity is a major determinant of adoption in that farmers who are more aware of water scarcity, are more likely to adopt more, and more advanced, water-saving irrigation techniques than those who are less aware. Another important outcome of the paper is that production risk and risk attitude affect the decision to adopt. Farmers who have experienced more production risk tend to adopt more. In line with this is the finding that risk-averse farmers are more likely to adopt more, and more advanced, techniques than risk-averse farmers. Apperently, adoption is seen as a way of hedging against production risks. The reason is that in China there are limited other ways of hedging against production risk, e.g. via crop insurance. Moreover, the more frequent and more serious droughts in the region induce risk-averse farmers to reduce the risks of crop losses by adopting water saving techniques.

Fourthly, social networks positively affect awareness of water scarcity. Apparently, farmers tend to have confidence in the opinions of their peers, water-user associations, neighbors and relatives on water scarcity and water saving techniques. Therefore, extension agencies ought to target social networks to promote irrigation water saving. The agencies may particularly want to focus on opinion leaders with a positive attitude towards adoption of water saving techniques in a bid to make their experiences and opinions spillover to other farmers.

Finally, investment in irrigation water saving techniques implies financial outlays that are often beyond the means of most farmers in the Guanzhong Plain. In addition, the possibilities for farmers to obtain credit on feasible terms are limited. Therefore, an important policy handle is improvement of accessibility to credit for investment in water saving techniques.

Efficient use of irrigation water is a prerequisite for sustainable agriculture in the Guanzhong Plain, but also for sustainable economic development at present levels in the region. Because of climate change with more frequent and more severe droughts, increasing industrialization and growing household income, the demand for water will rapidly increase which will further increase the need for irrigation water saving. Since it is a major wheat and corn producing region in Northern China which in its turn is China's main 'breadbasket', sustainable agriculture in the Guanzhong Plain is a prerequisite for nationwide food security, as well as for social and political stability. Hence, improving irrigation water use extends far beyond the agricultural sector's sustainable development. Adoption of water saving irrigation techniques is crucial in this process.

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Chapter 6

Estimation of the Impacts on Technical and Allocative Efficiency of their Determinants. SUR or SEM?[47]

Abstract: In this paper we compare estimation of the coefficients on irrigation water technical and allocative efficiency of their determinants by means of structural equation modeling (SEM) and seemingly unrelated regression (SUR). The former approach takes the efficiency measures as indicators of the underlying latent variable efficiency; the latter as separate dependent variables, but accounts for possible common factors that influence the error terms in the different equations. We compare estimation results of the two approaches based on a data set on single factor irrigation water use efficiency obtained from a survey of 360 farmers in the Guanzhong Plain, China. The main findings are: (i) model choice and efficiency measure affect the sign, significance, and magnitude of the coefficients; (ii) since it accounts for measurement error, reduces multicollinearity, and produces reliability coefficients, SEM is preferable to SUR.

JEL classification: C30 C51 C52 Q15

Keywords: Latent variable, Structural equation modeling (SEM), Seemingly unrelated regressions (SUR), Irrigation water allocative efficiency, Irrigation water technical efficiency

[47] Chapter based on: Tang, J., Folmer, H. Estimation of the impacts on irrigation water technical and allocative efficiency of their determinants. SUR or SEM? *Journal of Agricultural Economics*. Under Review.

6.1 Introduction

The definition of economic efficiency was introduced by Farrell (1957) and has triggered extensive research on its measurement ever since (Kopp, 1981; Kumbhakar and Lovell, 2000; Greene, 2008, among others). According to Farrell, overall efficiency, later renamed economic efficiency, is a composite concept (product) made up of technical and allocative efficiency. The former is a decision maker's ability to produce a given amount of output using the minimum amount of inputs while the latter is the ability to choose the optimal set of the inputs to produce a give output, given prices. Single factor allocative and technical efficiency are defined by analogy with the overall measures (Kopp 1981; Reinhard et al., 1999; Tang et al., 2014).

From the above definitions, it follows that efficiency is a psychological trait (ability) and thus inherently unobservable. That is, it is a theoretical construct or latent variable. Hence, it can be only measured indirectly via observed behavior or indicators, though with measurement error (Folmer and Oud, 2008; Oud and Folmer, 2008). Most researchers tend to ignore that efficiency is a latent variable and focus their theoretical and empirical analyses on the observable indicators instead. To the best of our knowledge, only three papers have treated efficiency as a (kind of) latent variable. Following Bollen (1989), Kalaitzandonakes et al. (1992) analyzed the relationship between farm size and technical efficiency by means of a structural equation model with latent variables (SEM) of the Multiple Indicator Multiple Cause (MIMIC) type (Bollen, 1989; Jöreskog and Goldberger, 1975). The author considers three indicators of the latent variable technical efficiency, viz. technical efficiency scores derived through (i) deterministic parameter frontier analysis, (ii) stochastic parameter frontier analysis, and (iii) nonparametric frontier analysis.[48] Kalaitzandonakes and Dunn (1995) use the same three indicators to analyze the relationship between education and technical efficiency. Richards and Jeffrey (2000) also applied the MIMIC model to analyze the factors that contribute to economic performance. The indicators of the latent variable performance are allocative, technical and overall efficiency.

[48] The authors found that the technical efficiency rankings based on the three indicators are not robust to estimation procedure. They ascribed this finding to the fact that the alternative technical efficiency measures had been measured with errors. They turned to SEM to take measurement error into account and to reconcile the conflicting outcomes.

The above three papers did not look into the performance of SEM compared to alternative (conventional) estimation procedures that do not treat efficiency as a latent variable but estimate the impacts of their determinants on the indicators instead. A typical example of the latter in the case of two or more indicators is Seemingly Unrelated Regression (SUR) which accounts for possible common factors that influence the error terms in the different equations. The purpose of the present paper is to fill this gap. It also intends to show that SEM is a convenient way to determine the most reliable indicator of the latent variable efficiency, i.e. allocative or technical efficiency. For this purpose we analyze by SEM and SUR a data set on irrigation water use efficiency obtained from a survey of 360 farmers in the Guanzhong Plain, China (Tang et al., 2014). Rather than on overall efficiency, this study focuses on single factor (irrigation water) efficiency. Single-factor technical efficiency refers to the ratio between actual input and the minimum feasible use of an input, keeping other inputs and output constant. This concept is applied in Lilienfeld and Asmild (2007) and Frija et al. (2009) to measure irrigation water technical efficiency. However, the “allocative” component of efficiency, single-factor allocative efficiency, has received little attention in the literature. It is the ratio between the optimized cost (when all inputs are technically and allocatively efficient) and the cost when the single-factor is technically efficient, keeping other inputs constant (Kopp, 1981; Kopp and Diewert, 1982). Both single-factor (irrigation water) technical and allocative efficiency are considered in this paper.

The organization of the paper is as follows. Section 6.2 presents the conceptual model including a brief summary of SEM. Sections 6.3 discusses the data and the empirical results. Section 6.4 concludes.

6.2 The conceptual model

Before turning to the conceptual model, we present a brief summary of SEM which can simultaneously handle, within one model framework, latent variables and their indicators. A SEM consists of two sub-models: two measurement models (equations (1) and (2) below) and a structural model (equation 3) (Jöreskog 1977; Jöreskog and Sörbom, 2001). The measurement model specifies the relationship between the latent variables and their observed indicators[49] while the structural model represents the relationships between the latent exogenous and latent endogenous variables as well as the relationships among the latent endogenous variables. Specifically:

$$\mathrm{y} = \Lambda_y \eta + \varepsilon \quad (1)$$

$$\mathrm{x} = \Lambda_x \xi + \delta \quad (2)$$

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta \quad (3)$$

where y and x are $\mathrm{p} \times 1$ and $\mathrm{q} \times 1$ vectors of endogenous and exogenous observed variables, respectively. Λ_y and Λ_x are $\mathrm{p} \times \mathrm{m}$ and $\mathrm{q} \times \mathrm{n}$ matrices of regression coefficients or loadings of the $\mathrm{m} \times 1$ and $\mathrm{n} \times 1$ vectors of latent endogenous and exogenous variables, η and ξ, respectively. The element β_{ij} of the $\mathrm{m} \times \mathrm{m}$ matrix B represents the effect of the *j*th endogenous latent variable on *i*th endogenous latent variable, and the element γ_{ij} of the $\mathrm{m} \times \mathrm{n}$ matrix Γ the effect of the *j*th exogenous latent variable on *i*th endogenous latent variable. Finally, ε, δ are $\mathrm{p} \times 1$ and $\mathrm{q} \times 1$ vectors of measurement errors of y and x, respectively, and ζ is the $\mathrm{m} \times 1$ vector of structural errors. For identification, estimation, testing and modification indices we refer to Jöreskog and Sörbom (2001).

Folmer and Oud (2008) discuss the theoretical and empirical advantages of using SEM. Particularly, they show that SEM allows a closer correspondence between theory and empirics than a model in observables only. Furthermore, SEM allows decomposition of the variance of an observed variable into the variance of the true (latent) variable and measurement error, as shown in equations (1) and (2). Note that measurement error in an explanatory increases the error variance, if the error is uncorrelated with the observed measure, and to attenuation bias, if it is correlated. Furthermore, if there is measurement error in the dependent, the estimator may be biased, if the error is correlated with the explanatory variables; if it is uncorrelated with the explanatory variables, it will lead to larger error variance. Since it purges measurement error of the latent variable, SEM reduces the measurement error problems. The use of SEM may also reduce multicollinearity (Folmer, 1981). Finally, SEM provides information about the reliability of the indicators.

[49] Note that directly observed variables can be conveniently handled in the SEM framework by specifying an identity relationship in the measurement model between an observed variable and the corresponding latent variable.

The conceptual SEM and SUR models are presented in Figures 6.1 and 6.2, and equations (4) –(6) and (8)–(10), respectively. *IWTE* and *IWAE* indicate single factor irrigation water technical efficiency and single factor irrigation water allocative efficiency, respectively. They are obtained from a stochastic frontier model (Tang et al., 2014). Both are functions of a latent variable, *Perception* (farmer's perception of water scarcity), the farmer characteristics *Age*, *Education*, *Income*, and *Time* (the proportion of time a farmer spends on farming), the farm characteristics *Fragmentation* (number of different plots) and *Infrastructure* (dummy variable that takes the value 1 if the irrigation canal is cement, and 0 if it is earthen-lined) and the variables *Waterprice* and *Precipitation*. For details on the variables, including measurement of the latent variable *Perception*, we refer to Tang et al. (2014). In SEM, *IWTE* and *IWAE* are taken as indicators of the latent variable *Efficiency* whereas in SUR they are treated separately. Note that SUR is a special case of SEM case. Hence, it can be specified as a SEM and estimated by SEM software packages.

Figure 6.1 Path diagram of the SEM model

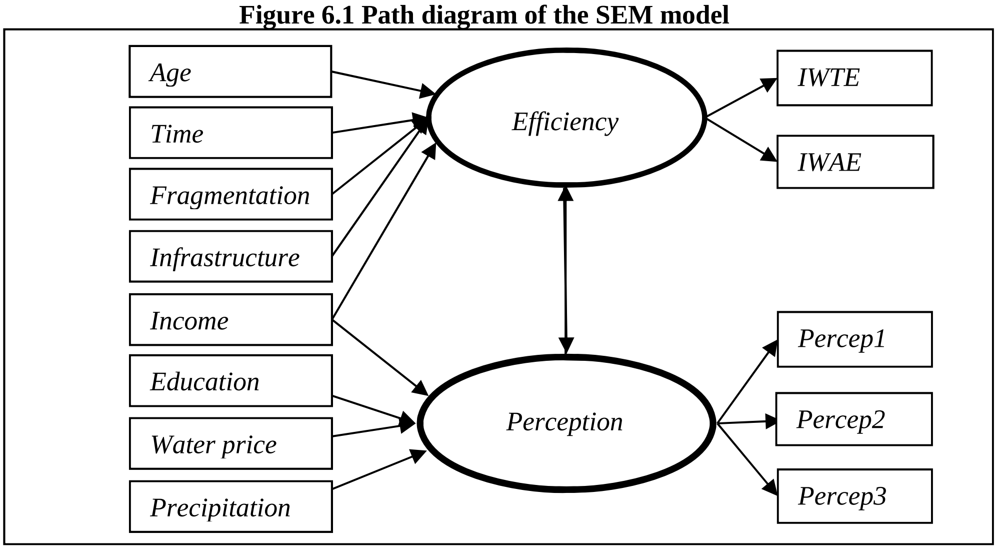
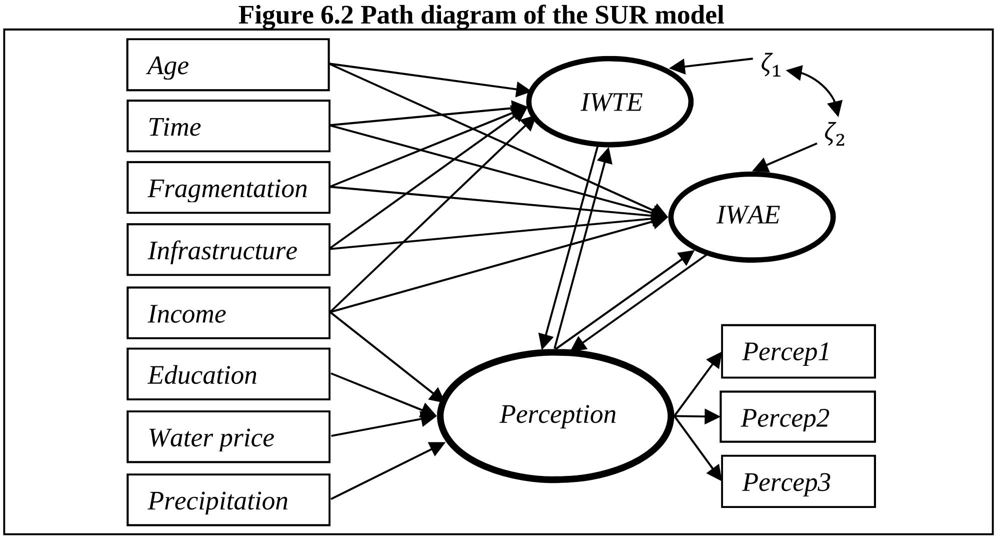


Figure 6.2 Path diagram of the SUR model



In terms of equations (1) and (3), the models presented in Figures 6.1 and 6.2 read as follows:

SEM:

$$\begin{bmatrix} IWTE \\ IWAE \\ Percep1 \\ Percep2 \\ Percep3 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 0 & \lambda_{3,2} \\ 0 & \lambda_{4,2} \\ 0 & \lambda_{5,2} \end{bmatrix} \begin{bmatrix} Efficiency \\ Perception \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{bmatrix} \tag{4}$$

$$\begin{bmatrix} Age \\ Time \\ Fragmentation \\ Infrastructure \\ Income \\ Education \\ Water\ price \\ Precipitation \end{bmatrix} = \begin{bmatrix} 10000000 \\ 01000000 \\ 00100000 \\ 00010000 \\ 00001000 \\ 00000100 \\ 00000010 \\ 00000001 \end{bmatrix} \begin{bmatrix} Age \\ Time \\ Fragmentation \\ Infrastructure \\ Income \\ Education \\ Water\ price \\ Precipitation \end{bmatrix} \tag{5}$$

$$\begin{bmatrix} Efficiency \\ Perception \end{bmatrix} = \begin{bmatrix} 0 & \beta_{1,2} \\ \beta_{2,1} & 0 \end{bmatrix} \begin{bmatrix} Efficiency \\ Perception \end{bmatrix}$$

$$+ \begin{bmatrix} \gamma_{1,1} & \gamma_{1,2} & \gamma_{1,3} & \gamma_{1,4} & \gamma_{1,5} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \gamma_{2,5} & \gamma_{2,6} & \gamma_{2,7} & \gamma_{2,8} \end{bmatrix} \begin{bmatrix} Age \\ Time \\ Fragmentation \\ Infrastructure \\ Income \\ Education \\ Water\ price \\ Precipitation \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \end{bmatrix} \tag{6}$$

SUR:

$$\begin{bmatrix} IWTE \\ IWAE \\ Percep1 \\ Percep2 \\ Percep3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \lambda_{3,1} \\ 0 & 0 & \lambda_{4,1} \\ 0 & 0 & \lambda_{5,1} \end{bmatrix} \begin{bmatrix} IWTE \\ IWAE \\ Perception \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{bmatrix} \tag{7}$$

$$\begin{bmatrix} Age \\ Time \\ Fragmentation \\ Infrastructure \\ Income \\ Education \\ Water\ price \\ Precipitation \end{bmatrix} = \begin{bmatrix} 10000000 \\ 01000000 \\ 00100000 \\ 00010000 \\ 00001000 \\ 00000100 \\ 00000010 \\ 00000001 \end{bmatrix} \begin{bmatrix} Age \\ Time \\ Fragmentation \\ Infrastructure \\ Income \\ Education \\ Water\ price \\ Precipitation \end{bmatrix} \tag{8}$$

$$\begin{bmatrix} IWTE \\ IWAE \\ Perception \end{bmatrix} = \begin{bmatrix} 0 & 0 & \beta_{1,3} \\ 0 & 0 & \beta_{2,3} \\ \beta_{3,1} & \beta_{3,2} & 0 \end{bmatrix} \begin{bmatrix} IWTE \\ IWAE \\ Perception \end{bmatrix}$$

$$+ \begin{bmatrix} \gamma_{1,1}\gamma_{1,2}\gamma_{1,3}\gamma_{1,4}\gamma_{1,5} & 0 & 0 & 0 \\ \gamma_{2,1}\gamma_{2,2}\gamma_{2,3}\gamma_{2,4}\gamma_{2,5} & 0 & 0 & 0 \\ 0 \quad 0 \quad 0 \quad 0 & \gamma_{3,5}\gamma_{3,6}\gamma_{3,7}\gamma_{3,8} \end{bmatrix} \begin{bmatrix} Age \\ Time \\ Fragmentation \\ Infrastructure \\ Income \\ Education \\ Water\ price \\ Precipitation \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \end{bmatrix} \tag{9}$$

$$\Psi = \begin{pmatrix} \psi_{11} & & \\ \psi_{21} & \psi_{22} & \\ & & \psi_{33} \end{pmatrix} \tag{10}$$

Equations (4) and (5) and (7) and (8) are the endogenous and exogenous SEM and SUR measurement models, respectively; equation (6) and (9) the structural SEM and SUR models, respectively. Equation (10) is the covariance matrix of ζ. The off-diagonal element ψ_{21} shows the covariance between the errors of the structural models ζ_1 and ζ_2.

6.3 Data and empirical results

We analyze a data set of 360 farmers in the Guanzhong Plain, China. It was collected via a face-to-face interview in October, 2011. The sampling scheme was stratified random sampling. The SUR model was estimated in Tang et al. (2014). Before discussing the estimates, we make the following remarks. First, a measurement scale was assigned to the latent variables (which is a prerequisite for identification) by fixing their variances (at 1). Secondly, we standardized the coefficients which implies that they represent the standard deviation changes in the dependent variable due to standard deviation changes in the explanatory variables. This makes the coefficients directly comparable. Thirdly, because of the presence of ordinal variables, we analyzed a polychoric correlation matrix. Finally, we estimated the models by means of LISREL 8.8 (Jöreskog and Sörbom, 2001).

The measures of model fit of both models are presented in Table 6.1. The p-values corresponding to the χ^2 statistics indicate the probability of obtaining a sample as the one at hand, if the hypothesized conceptual model is true. The *p*-value for SUR is larger than for SEM, which indicates that SUR fits the data better than its alternative.[50] The other statistics in Table 6.1 indicate good overall fit for each of the two models, since they meet their critical values by wide margins. Except for the RMSA, the SUR goodness of fit statistics are slightly better than for SEM.

Table 6.1 Goodness of fit statistics

	χ^2	NFI	GFI	AGFI	RMSEA
SEM	46.83(df=34, p=0.0704)	0.900	0.980	0.945	0.033
SUR	34.54(df=28, p=0.1835)	0.926	0.985	0.951	0.026

Note: The cut-off values for NFI, GFI, AGFI and RMSEA indicating a good fit are 0.90, 0.95, 0.90 and 0.06, respectively (Hooper et al., 2008). The higher the NFI, GFI and AGFI values are and the smaller the RMSEA is, the better is the fit.

The standardized coefficients of the indicators of *Perception* in *SEM* and *SUR* differ slightly and are all significant. Moreover, the reliabilities (R^2) are above the recommended level of 0.20 (Jöreskog and Sörbom, 2001), indicating that the three indicators measure *Perception* well. The most reliable indicator is *Percep1*, followed by *Percep2*, and *Percep3*. Apparently, perception of the present and past situation, as measured by the first 2 indicators, is more reliable than perception of the future, as expected. Table 6.2 also shows that *IWTE* and *IWAE* are significant indicators of *Efficiency* with the former the most important and most reliable.

Table 6.2 Measurement model(standardized coefficients)

Variables	Indicators	*SEM*			*SUR*		
		Coeff.	t	R^2	*Coeff.*	t	R^2
Perception	*Percep1*	0.817***	8.070	0.69	0.834***	6.682	0.66
	Percep2	0.538***	7.193	0.28	0.529***	6.174	0.29
	Percep3	0.483***	6.701	0.22	0.473***	5.826	0.23
Efficiency	*IWTE*	0.777***	4.444	0.61	----	----	----
	IWAE	0.372***	3.961	0.14	----	----	----

Note: *p<.10, **p<.05, ***p<.01.

The structural models are presented in Table 6.3. The table shows that *Efficiency* (SEM), and *IWTE* and *IWAE* (SUR) impact *Perception* negatively and significantly. In addition, the coefficient of *Efficiency* (-0.686) is larger than those of *IWTE* (-0.361) and *IWAE* (-0.568). In both models, the impacts of the exogenous variables on *Perception* have the same sign and are all significant, though the sizes differ marginally to moderately.

[50] Note that the p-value corresponding to the χ^2 statistic tends to be depressed, if the distribution of the observed variables deviates from normality (Bollen, 1989). Furthermore, SEM and SUR are non-nested which implies that formal tests based on their χ^2 values are not possible.

Table 6.3 The estimated *SEM* and *SUR* (standardized coefficients)

	SEM		*SUR*		
Variables	*Perception*	*Efficiency*	*Perception*	*IWTE*	*IWAE*
IWTE		----	-0.361* (0.202)	----	----
IWAE		----	-0.568*** (0.186)	----	----
Efficiency	-0.686*** (0.231)	----	----	----	----
Perception	----	0.521** (0.240)	----	0.326 (0.246)	0.770** (0.360)
Age	----	0.089 (0.084)	----	0.071 (0.064)	0.093 (0.075)
Education	0.057 (0.068)	----	0.036 (0.067)	----	----
Time	----	-0.169* (0.087)	----	-0.135** (0.065)	-0.104 (0.076)
Fragmentation	----	-0.137* (0.079)	----	-0.108 (0.066)	-0.143* (0.078)
Infrastructure	----	0.250*** (0.082)	----	0.172** (0.072)	0.205** (0.086)
Income	-0.067 (0.077)	0.201** (0.083)	-0.095 (0.074)	0.145** (0.071)	0.162* (0.084)
Waterprice	0.190*** (0.070)	----	0.179*** (0.068)	----	----
Precipitation	-0.241*** (0.071)	----	-0.300*** (0.070)	----	----
R^2	0.490	0.228	0.496	0.128	0.385

Note: Standard errors in parenthesis.
*p<.10, **p<.05, ***p<.01.

For the reverse effects from *Perception* on *Efficiency* and *IWTE* and *IWAE* we find a difference between SEM and SUR. Specifically, *Perception* impacts *Efficiency* positively and significantly (0.521). The impact of *Perception* on *IWAE* is also positive and significant but insignificant on *IWTE,* though positive.

Regarding the exogenous variables, there are three classes of variables. First, variables with coefficients that have the same sign and are significant in both models, although size differs. The variables that belong to this class are *Infrastructure, Income, Waterprice* and *Precipitation*. For the second class, the significance levels differ between the two models. Specifically, *Time* and *Fragmentation* are both significant in *SEM* while in *SUR* the impact of *Time* on *IWAE* is insignificant while *Fragmentation* insignificantly affects *IWTE*. The third class includes *Age* and *Education*, which are insignificant in both models.

Table 6.3 gives an incomplete overview of the impacts of the various variables on *IWTE* and *IWAE* because the indirect effects are not taken into account. Consequently, comparison of SEM and SUR is not quite well possible. To overcome this problem, we present in Table 6.4 the total effects (i.e. the sum of the direct effect (the coefficients in

Table 6.3) and the indirect effects) of all variables on *Perception*, *Efficiency* and *IWTE* and *IWAE*.

Table 6.4 Estimated total effects (standardized coefficients)

Variables	Perception	Efficiency	IWTE	IWAE	Perception	IWTE	IWAE
IWTE	----	----	----	----	-0.232* (0.141)	-0.076 (0.087)	-0.179* (0.093)
IWAE	----	----	----	----	-0.365*** (0.078)	-0.119 (0.074)	-0.281* (0.157)
Perception	-0.263* (0.179)	0.384*** (0.103)	0.298** (0.135)	0.143** (0.061)	-0.357** (0.150)	0.210 (0.133)	0.495*** (0.123)
Efficiency	-0.505*** (0.080)	-0.263* (0.149)	0.573*** (0.104)	0.274*** (0.063)	----	----	----
Age	-0.045 (0.043)	0.066 (0.065)	0.051 (0.048)	0.024 (0.024)	-0.051 (0.037)	0.054 (0.055)	0.055 (0.050)
Time	0.085* (0.045)	-0.125* (0.073)	-0.097* (0.050)	-0.046* (0.027)	0.069* (0.039)	-0.112** (0.056)	-0.051 (0.051)
Fragmentation	0.069 (0.042)	-0.101* (0.060)	-0.079* (0.046)	-0.038 (0.024)	0.077** (0.037)	-0.082 (0.052)	-0.083* (0.046)
Infrastructure	-0.126*** (0.047)	0.184*** (0.067)	0.143*** (0.047)	0.068** (0.028)	-0.115*** (0.040)	0.134** (0.052)	0.116** (0.047)
Income	-0.151** (0.063)	0.122* (0.071)	0.095* (0.052)	0.046 (0.029)	-0.154** (0.064)	0.095* (0.053)	0.043 (0.053)
Education	0.042 (0.051)	0.022 (0.027)	0.017 (0.022)	0.008 (0.010)	0.023 (0.043)	0.008 (0.016)	0.018 (0.033)
Water price	0.140** (0.059)	0.073** (0.032)	0.057* (0.032)	0.027* (0.015)	0.115** (0.054)	0.037 (0.027)	0.089** (0.038)
Precipitation	-0.177*** (0.064)	-0.092*** (0.034)	-0.072** (0.036)	-0.034* (0.017)	-0.193* (0.070)	-0.063 (0.042)	-0.149*** (0.045)

Note: Standard errors in parenthesis.
$^{*}p<.10$, $^{**}p<.05$, $^{***}p<.01$.

The total effects on *Perception* and their significance levels only differ marginally between the two models. We rank the variables with significant total effects by size.[51] For SEM the ranking is *Precipitation* (-0.177), *Income* (-0.151), *Waterprice* (0.140), *Infrastructure* (-0.126) and *Time* (0.085). Compared to SEM, the only difference for SUR is that *Fragmentation* is significant and ranks higher than *Time*.

We now turn to the total effects on *IWTE* and *IWAE*. Note that in *SEM* the total effects on *IWTE* and *IWAE* are the effects of the exogenous and endogenous variables via *Efficiency* while in SUR the effects are direct from the exogenous variables. Regarding *IWTE*, in SEM seven variables have significant total effects[52]: *Perception* (0.298), *Infrastructure* (0.143), *Time* (-0.097), *Income* (0.095), *Fragmentation* (-0.079), *Precipitation* (-0.072) and *Waterprice* (0.057). However, only three variables have significant total effects on *IWTE* in SUR: *Infrastructure* (0.134), *Time* (-0.112) and

[51] The rankings are based on absolute values.
[52] We do not discuss the total effects of the latent variable Efficiency because it does not exist in SUR and no comparison can be given.

Income (0.095). The signs of the variables with insignificant total effects are robust across both models, however. Regarding *IWAE,* the five variables with significant total effects in SEM are: *Perception* (0.143), *Infrastructure* (0.068), *Time* (-0.046), *Precipitation* (-0.034), *Waterprice* (0.027). In SUR *Time* is not significant while *Fragmentation* is. The ranking in SUR is: *Perception* (0.495), *Precipitation* (-0.149), *Infrastructure* (0.116), *Waterprice* (0.089), *Fragmentation* (-0.083).

6.4 Conclusions

The purpose of this paper is to investigate effects of model choice on the coefficients of the determinants of single factor irrigation water technical efficiency (*IWTE*) and single factor irrigation water allocative efficiency (*IWAE*). The comparison relates to structural equation model (SEM) and seemingly unrelated regression (SUR). One conclusion that emerges from the comparison is that model choice, SEM or SUR, indeed tends to affect the coefficients. Only in the case of “large” coefficients the results tend to be robust in terms of sign and significance, though the size usually varies marginally to moderately. This conclusion is in line with Kalaitzandonakes et al. (1991) who find that technical efficiency ranking of farms may not be robust to estimation procedure. Another finding of this paper is that the coefficients are not robust to efficiency measure analyzed, which was also observed by Kalaitzandonakes and Dunn (1995).

Kalaitzandonakes et al. (1992) recommend *SEM* to reconcile dissimilar efficiency scores by taking them as indicators of a latent variable and to apply SEM. The findings in this note confirm this recommendation. We furthermore summarize several additional reasons to apply SEM including a closer correspondence between theory and empirics, accounting for measurement error and reduction of multicollinearity. In addition, SEM produces reliability indices of the indicators. On the basis of these features, the conclusion emerges that in general SEM is preferable to SUR.

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Chapter 7

Conclusions and discussions

This chapter presents main conclusions (section 7.1) and policy recommendations (section 7.2) from chapters 2-6. In addition, it discusses some limitations of the research and offers some suggestions for future research.

7.1 Main empirical findings

This section is organized by the main research objectives specified in section 1.4. Note that the analysis of sub-objective one is based on a panel data set of 800 farmers in the Guanzhong Plain for the period 2000-2005, collected by Northwest A&F University, China. The analysis of sub-objectives 2-5 are based on a cross sectional data set of 460 farmers in the same area collected by the author.

As mentioned in Chapter 1, the main objective of the thesis is to measure irrigation water use efficiency in the Guanzhong Plain. From this overall objective 5 sub-objectives were derived. The main conclusions per sub-objective are the following.

(i) Analysis of the impacts of management reform on technical efficiency of irrigation water use

This sub-objective was the main theme of Chapter 2. As a first step, I measured single factor irrigation water technical efficiency (below I just speak of irrigation water technical efficiency or just efficiency, if there is no risk of confusion) by means of a stochastic frontier analysis. The outcome of this analysis is that irrigation water use efficiency is very is low. The overall yearly average over the period 2000-2005 is 0.1577. It was extremely low at the beginning of the research period with the lowest value of 0.0795 in 2000. During the research period the situation improved. The yearly average increased from 0.1063 in 2001 to 0.2316 in 2005. The low efficiency indicates that, ceteris paribus, output can be maintained while using less irrigation water. For instance, in 2005, almost 77 per cent of irrigation water could have been saved while keeping current level of output and other inputs than water constant.

A second result is that all three management types, i.e., private company, joint-stock co-operative, and water users' association, have substantially improved irrigation water use technical efficiency. This is due to the fact that the reform, irrespective of management type, has transferred canal management responsibilities to institutions that have incentives to improve the performance of the irrigation system, and thus of water use efficiency. Under the reform, waste incurred during transportation or because of mismanagement is the own responsibility of the institutions. Hence, they have incentives to save water via improving infrastructure and management techniques. We further found that water users' association is the most successful management form, followed by joint-stock co-operative and private company. The explanation is that of the three management types, water users' associations allow most farmer participation. Particularly, in water users' associations farmers are involved in virtually all decisions on irrigation issues through regular meetings. Consequently, they have a high willingness to invest in irrigation infrastructure and irrigation services. In a second stage analysis, I estimated the impacts of several control variables on irrigation water use efficiency by way of a Tobit model. The main outcome was that water price and disclosure, have the largest impacts. Specifically, a price increase of, say, 10 per cent leads to an increase of efficiency by 0.4 percentage points. The rationale is that a higher price induces farmers to reduce costs and thus to save water. The impact of disclosure is also positive and highly significant. The information disclosed includes irrigated area, water fee paid and volume of water used per farmer. The main rationale for the positive impact is that information on water use by other farmers serves as a benchmark and incentive to improve a farmer's water use efficiency.

Finally, the efficiencies of irrigation water use at both micro (farm) and regional (canal) level were compared. Canal data were obtained by aggregating the data for the farmers belonging to the same canal. The two-stage estimation procedure, viz. stochastic frontier analysis and Tobit regression, was also applied to canal data. Overall average technical efficiency over the 6-year period was found to be 0.4877, far above the farmer level overall average of 0.1577. Apparently, aggregation leads to an upward bias due to ignoring heterogeneity among individuals. In the second stage analysis, the canal model turned out to be less clear-cut than the farmer model, which is related to the smaller number of observations. Therefore, we conclude that micro level analysis is preferable to macro/aggregate level analysis in explaining behavior.

(ii) Awareness and perception of irrigation water scarcity

The second research question relates to the formation of farmers' awareness and perception of irrigation water scarcity. The question was addressed in Chapter 3. Perception of water scarcity is defined as the recognition of the state of water availability as problematic in the home village whereas awareness refers to the concern (mindful and heedful) about its impacts on output. Perception of water scarcity was measured by four indicators and awareness by three. The descriptive statistics showed that the vast majority of the respondents are aware of the impacts of water shortage, although most of them do not perceive water scarcity in their home village yet.

Secondly, we analyzed the relationship between perception and awareness by means of a structural equation model (SEM). The results showed that perception is a prerequisite for growing awareness and, vice versa, that awareness promotes and facilitates perception. This also follows from the descriptive statistics. Specifically, only 47% of the respondents who think irrigation water is not scarce report worry about water shortage. However, among the farmers who believe that irrigation water is scarce, 83% state that they are worried.

In addition to their interdependence coefficients, the impacts of several exogenous variables on perception and awareness were estimated. The exogenous variable with the largest effect on awareness of water scarcity was social network. Access to media had no effect, however. This indicates that farmers' contacts with their neighbors, irrigation managers, water saving extension agencies and other farmers, play an effective role in creating awareness. The more connected he (she) is to social networks with knowledge of water scarcity, the larger the likelihood that a farmer will perceive irrigation water as scarce and think that water saving is important. This finding is consistent with Scherer and Cho's (2003) assertion that perception of hazards is shared through social linkages in the first place. The fact that access to media has no effect on awareness of irrigation water scarcity is probably due to low media exposure in the area or to the fact that the media pay little attention to it.

Another important finding of Chapter 3 is that water price positively and significantly relates to perception and awareness, confirming the hypothesis that water price signals water scarcity. We also found that older farmers are less heedful about water shortage than their younger peers. This is because compared to old farmers, young farmers have a longer expected remaining lifespan, and thus, larger expected remaining lifetime earnings. Moreover, the farmer who has more prior experiences with water scarcity and who spends more time on farming, is more awareness of water scarcity.

(iii) The impacts of perception on technical and allocative efficiency of irrigation water use

Chapter 4 analyzed the third sub-objective which relates to the determinants of allocative and technical irrigation water use efficiency, particularly the impact of perception. As a first step, both types of efficiency were measured. Mean technical efficiency in 2010 was 0.35 which is low, though substantially higher than in 2005 when it was 0.23, as reported in chapter 2. Allocative efficiency is a farmer's ability to minimize cost using the optimal level of inputs. Its mean value was 0.86, indicating that not allocating the inputs at cost-minimizing proportions led to a total cost increase by 14%. The chapter furthermore showed that if irrigation water use were both technically and allocatively efficient (the ideal theoretical benchmark), total cost could be feasibly decreased by 20% while keeping output at the observed level. Since the cost of irrigation water accounted for only 9.85% of total cost, its price could be more than doubled (i.e. increased by 2.03 to give the feasible cost decrease of 20%), without hampering farmers' income, if irrigation water use were technically and allocatively efficient.

The impact of perception of irrigation water scarcity on allocative efficiency was found to positive and significant and positive, though insignificant at conventional levels, on technical efficiency. These results indicate that farmers with better perception of water scarcity use irrigation water more efficiently. Another interesting outcome was the reverse effect: efficient farmers have a more optimistic view of combating water scarcity via improving efficiency.

Farmers' age does not play a role in effecting water use efficiency. This outcome is probably due to the fact that irrigation requires little farming experience. Another finding is that the more time a farmer spends on farming, the less efficient he or she is in using irrigation water. This result collides with the hypothesis that part-time farmers are less efficient because they have off-farm income which renders farming activities, including irrigation, less important to them than to full time farmers. A possible explanation is that part-time farmers spend less time on farming which induces them to reduce the frequency of irrigations, particularly of redundant irrigations. In addition, each irrigation needs to be effective. Another finding is that adequate irrigation infrastructure increases water use efficiency. Half of the irrigation canals are in a poor state which leads to poor accessibility and loss of water when irrigating. Another important finding is that price indirectly (via perception) improve efficiency, as it signals water scarcity. Finally, land fragmentation was found to decrease efficiency while income increases it.

(iv) Adoption of irrigation techniques

Chapter 5 analyzed adoption of irrigation techniques in the Guanzhong Plain. A three-stage adoption model was constructed consisting of the following stages: (1) perception of water scarcity, (2) awareness of the existence of water saving techniques, and (3) intensity of adoption. For the first and second stage, farmers were found to be aware of the water scarcity problem and also of both traditional and advanced technologies. Furthermore, the adoption rate of water-saving techniques turned out to be high. Approximately 80% of the farmers use at least one household-based water-saving technique, i.e. border irrigation, furrow irrigation, surface pipe, drought-resistant variety, mulching, or fertigation. However, the traditional irrigation techniques such as furrow irrigation are still prevalent while the adoption rates of advanced techniques such as mulching, drought resistant varieties and pipelines are low. However, the vast majority of farmers are aware of their existence. Some farmers were found to combine advanced and traditional techniques.

In the analysis, we paid special attention to two risk factors, viz. production risk and attitude toward risk. One finding was that greater production risk leads to greater awareness of water-saving techniques and larger intensity of adoption. This is probably due to the limited possibilities in China to hedge against production risk, for instance, via crop insurance. Consequently, farmers rely to a large extent on themselves in mitigating risk. Therefore, they tend to resort to innovations to mitigate production risk. For that purpose they collect information on innovations which enhances their awareness. Another important outcome was that risk attitude affects the decision to adopt. Risk-loving farmers are more likely to adopt more, and more advanced, techniques than risk-averse farmers. The reason is that adoption does not come without risk. Farmers will not adopt if they perceive too high a risk to offset the advantages of the adoption. A risk-loving attitude lowers the risk threshold. Moreover, a risk-loving farmer is likely to be more aware of irrigation innovations than a risk-averse farmer. This is probably due to the fact that a risk loving attitude stimulates interest in exploring new avenues and in information on new innovations.

Other factors were also found to play a role. Particularly, social networks positively affect awareness of water scarcity and of water-saving techniques. That is, farmers tend to have confidence in the opinions of their peers, neighbors and relatives on water scarcity and water saving techniques. Education positively and significantly impacts on awareness of irrigation techniques. Apparently, whereas for awareness of water scarcity one’s network suffices, awareness of water saving techniques requires more specialized knowledge for which education is required. Finally, financial status positively relates to adoption, because adoption implies investment costs.

(v) Estimation of the impacts of the determinants of technical and allocative efficiency: Seemingly Unrelated Regressions (SUR) or Structural Equations Modeling (SEM)?

This sub-objective is an offspring of sub-objective 3, viz. estimation of the impacts of perception on technical and allocative efficiency of irrigation water use. In chapter 4, we applied Seemingly Unrelated Regressions (SUR). An alternative approach is SEM. The latter takes technical and allocative efficiency as indicators of a latent variable, say efficiency, and estimates the total impacts of their determinants via the structural model and the endogenous measurement model rather than directly via the structural model, as in the case of SUR. One finding is that only in the case of “large” coefficients the results of both estimation procedures are robust in terms of sign and significance, though the size usually varies marginally to moderately. This conclusion is in line with Kalaitzandonakes et al. (1992) who find that technical efficiency ranking of farms may not be robust to estimation procedure. Another finding of this chapter is that the coefficients are not robust to efficiency measure analyzed, which was also observed by Kalaitzandonakes and Dunn

(1995). Kalaitzandonakes et al. (1992) recommend SEM to reconcile dissimilar efficiency measure scores by taking them as indicators of a latent variable and to apply SEM. Our findings confirm this recommendation.

7.2 Policy recommendations

The Chinese government is fully aware of the water scarcity problems in the country, as illustrated by former prime minister's observation that water shortage is threatening "the very survival of the Chinese nation" (see chapter 1) . The government has also developed strategies to reduce water scarcity. However, the strategies adopted so far are mainly supply-oriented water strategies rather than demand-oriented ones. They boil down to augmenting water supply by building dams and moving water from water abundant areas to the water-stressed areas. These projects are costly and are highly unlikely to solve the water scarcity problem in Northern China and elsewhere (Berkoff, 2003). Hence, alternative strategies need to be explored, particularly demand and institutional oriented strategies. However, these strategies are still in the "pilot" phase (Zhang et al., 2013).

In this thesis I have shown that agriculture, the sector which consumes most water, has a large water saving potential. Its efficiency can be improved by means of better institutional arrangements, particularly, irrigation management reform, water pricing and increasing water scarcity awareness.

(i) The thesis shows that management reform in general, particularly the introduction of joint-stock co-operatives and especially of water users' associations, has a substantial impact on efficiency. The main reason for their impact is farmer involvement in virtually all decisions on irrigation water management. Since the proportion of water users' associations and joint-stock co-operatives is still small, these management types should be strongly promoted by amongst others the provincial and local governments.

(ii) A second major policy conclusion is that a higher price will improve irrigation water efficiency, since it enhances awareness of water scarcity. In addition, water price has a direct impact on efficiency because it stimulates cost saving and hence water saving. So far the impact of water price has been very moderate. The reason is that the price charged for irrigation water in China is far below its marginal value. The rationale for sub-optimal prices is income policy. The income gap between rural and urban China has been widening substantially over the past decades. There is a widespread belief among Chinese policy-makers, but also elsewhere in the Chinese society, that a higher price for irrigation water is at odds with the objective of narrowing the rural-urban income gap (Johansson et al. 2002; Tsur et al. 2004). However, there is no evidence for this. On the contrary, at current efficiency levels income loss due to higher prices is offset by the savings due to efficiency gains. Note that 'right' prices and their impacts on irrigation water efficiency also contribute towards agriculture sustainability in the long run which may further contribute to their acceptance. Summarizing, water pricing should be revised towards prices that reflects the marginal value of water. In addition, it can be used as a policy handle to signal water scarcity.

A possible drawback of higher prices, as pointed out by Liao et al. (2008), is that some farmers may decide to give up farming. The drop out of farmers, however, is no problem because plots are currently far too small and there is too much labour in agriculture. Furthermore, reorganization of land offers more efficient farmers the possibility to expand their farms which is beneficial to both rural and urban China. Meanwhile, action should be taken to prevent that higher water prices induce farmers to switch to groundwater. However, the risk of such a switch is rather small because the pumping costs of groundwater have been increasing due to the fall of the water table.

(iii) A third policy recommendation is that extension should focus on stimulating awareness of water scarcity and of water saving techniques, particularly via social networks which have been found in this thesis to be very effective. Apparently, farmers tend to have confidence in the opinions of their peers, neighbors and relatives on these issues. Of special importance are key informants who can influence the opinion, awareness and perception in their networks and thus the behavior of their peers. Extension agencies may want to focus on risk-loving farmers with a positive attitude towards adoption of water saving techniques in a bid to make their experiences and opinions spillover to other farmers. A related policy suggestion is that extension agencies ought to design and implement programs aimed at risk aversion reduction by convincing farmers that adoption of WSTs actually reduces production risk rather than increases it. The reason is that a substantial proportion of farmers have been found to be risk-averse.

7.3 Limitations and suggestions for further research

The research undertaken in this thesis is subject to the following shortcomings. First, the sample is subject to sample selection. I applied four-stage stratified random sampling. The first strata is irrigation districts, followed by canals within the selected irrigation districts, followed by villages per canal and finally farmers per canal. The selection of farmers at the fourth stage was supposed to be random. However, the list of farmers to randomly sample from was incomplete in some cases. Moreover, in several cases farmers selected were not available due to part-time jobs outside the village, or even outside the province.

A second problem was inadequate measurement of the quantity of irrigation water used due to lack of adequate meters to gauge water withdrawn. Hence, the quantity used had to be estimated based on frequency of irrigations, duration per irrigation, canal size, and water fee paid. A majority of farmers were able to provide these pieces of information. For farmers who could not provide one or several of these pieces, observations on similar farmers were used to estimate the amount withdrawn. Hence, the calculation of water volume used is an estimate rather than a precise measurement. This may, to some extent, have affected the results, especially estimates of water use efficiency.

A third shortcoming is that I did not consider the costs nor technical feasibility of the irrigation techniques adopted. Insight into these aspects is needed for a comprehensive adoption analysis.

In chapter 2 I found that water users' association is the most efficient irrigation management form. In practice, however, water users' associations are not without limitations. Wang et al. (2010) concludes that a successful water users' association should meet the following five principles: adequate and reliable water supply, have legal status, have wide coverage and full farmer involvement, organization within hydraulic boundaries, volumetric measurement of deliveries, and equitable collection of water charges from members. I found that not all water users' associations meet these principles. In most water users' associations, the role of farmers in decision-making is limited because the village leaders or their representatives dominate the board. Furthermore, there is lack of farmer human capital because educated farmers tend to become migrant workers in the cities, leaving agriculture practices to women. In addition, due to lack of management experience, poor knowledge of irrigation techniques and limited interest due to small farm size, large groups of farmers are rather indifferent about joining a water users' association. Hence, the question how to improve membership and the functioning of water users' associations should be addressed in future research.

Secondly, the analysis focused on grain (wheat and corn) production for which price uncertainty plays a minor role. This is because grain price in China is very stable since it has huge grain reserves that can absorb price fluctuations. This does not hold for cash crops such as vegetables and fruits that are also produced in the Plain. A future study of cash crops which considers both production and price uncertainty is important.

Another limitation is that I did not distinguish between usage of groundwater and surface water. The basic question is if groundwater irrigation efficiency differs from surface water irrigation efficiency. This question is of growing importance for the North China Plain since the groundwater tables have been declining. There is evidence that groundwater is very inefficiently used because only a pumping fee but no water fee is paid (Webber, 2008; Wang et al., 2009). Furthermore, landowners can drill a well without permission from the government. So they can pump as much water as they want. Hence, waste is prevalent. It follows that regulation of the groundwater market is an important topic for future research.

Finally, this thesis focuses on the "quantity" side of China's water problem, the "quality" side is not considered. As mentioned in the Introduction, water pollution is another severe water issue in Northern China. Since awareness has been found to be crucial in increasing water use efficiency, we have ample reason to assume awareness of water pollution also has an effect on mitigating water pollution. Thus, awareness of water pollution, is an interesting topic and worth further investigation.

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Summary

While water is scarce in northwestern China, the demand for it is growing rapidly due to population and income growth, industrialization and urbanization. Due to insufficient precipitation, irrigation plays a crucial role in ensuring agricultural production and food security in the region and China as a whole. Despite its scarcity, irrigation water use efficiency is low because of weak water management. Hence, this thesis focuses on demand and institutional oriented strategies to improve irrigation water use efficiency. It analyzes the impacts of several policy handles, notably irrigation water management reform, water pricing, stimulation of the adoption of water-saving techniques, and enhancement of farmers' awareness of water scarcity, on farmers' irrigation water use efficiency.

Data analyzed includes a panel data set of 800 farmers for the period 2000-2005, and a cross-sectional data set of 460 farmers collected in 2011 in the Guanzhong Plain. The main conclusions are the following. Firstly, irrigation management reform has a positive impact with water users association having the largest effect, followed by joint-stock co-operative and private company. Secondly, enhancing awareness of water scarcity is effective in increasing irrigation water efficiency and adoption of water-saving techniques. Thirdly, dissemination of information via social networks, rather than via the media, is an important vehicle to enhance awareness of water scarcity. Fourthly, risk-averse farmers who have experienced production risk are more likely to adopt more, and more advanced water-saving techniques.

Nederlandse Samenvatting

Terwijl in het noordwesten van China water schaars is, neemt de vraag ernaar snel toe vanwege bevolkingsgroei, inkomensstijging, industrialisatie en verstedelijking. Omdat neerslag ontoereikend is, speelt irrigatie een cruciale rol in de landbouw, zowel in de regio als in China als geheel. Echter, ondanks waterschaarste is irrigatie inefficiënt.

Dit proefschrift analyseert vraaggeoriënteerde en beheergeoriënteerde beleidsmaatregelen om de efficiëntie van irrigatiewatergebruik te verbeteren in de Guanzhong vlakte. De effecten van de volgende beleidsinstrumenten worden geanalyseerd: hervorming van irrigatiewaterbeheer, de prijs van water, stimulering van het gebruik van waterbesparende technieken en bevordering van de bewustwording van boeren van water schaarste.

De geanalyseerde gegevens zijn paneldata van 800 boeren voor de periode 2000-2005 en cross-sectie data van 460 boeren die in 2011 zijn geënquêteerd. De belangrijkste conclusies zijn de volgende. Ten eerste, hervorming van irrigatiewaterbeheer heeft een positief efficiency effect. Verenigingen van watergebruikers hebben het grootste effect, gevolgd door naamloze vennootschappen en private ondernemingen. Ten tweede heeft stimulering van het bewustzijn van waterschaarste een positief effect. Ten derde, verspreiding van informatie via sociale netwerken is een belangrijk middel om de bewustwording van waterschaarste te bevorderen. Ten vierde, zowel boeren die risico afkerig zijn als boeren die ervaring hebben met productierisico's, zijn geneigd zich meer, en meer geavanceerde, waterbesparende technieken eigen te maken.